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Career Placement of Skilled Migrants in the U.S. Labor Market

A Dynamic Approach

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Abstract

The initial occupational placements of male immigrants in the U.S. labor market vary significantly by country of origin even when education and other factors are taken into account. Does the heterogeneity persist over time? Using data from the 1980, 1990, and 2000 U.S. Censuses, this study finds that the performance of migrants from countries with lower initial occupational placement levels improves at a higher rate compared with that of migrants originating from countries with higher initial levels. Nevertheless, the magnitude of convergence suggests full catch-up is unlikely. Country specific attributes are found to have less direct impact on the rate of assimilation than on the initial performance.

This paper—a product of the Trade Team, Development Research Group—is part of a larger effort in the department to research determinants and implications of migration. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at ineagu@worldbank.org.

Career Placement of Skilled Migrants in the U.S. Labor Market: A Dynamic Approach

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1. INTRODUCTION

The extensive research on US immigrants varies greatly in findings. Some studies provide optimistic depictions of immigrants' performance on the US labor market[1], while others question whether convergence between immigrants' and natives' performance occurs at all.[2] This paper investigates the convergence among country of origin performance patterns of skilled male migrants to the US. Relying on Censuses 1980, 1990 and 2000 it attempts to answer three questions. First, do the entry levels of occupational placement of skilled US migrants differ by country of origin when other factors are kept constant? Second, how does occupational placement by country of origin change over time? Finally, to what extent do country of origin attributes explain the temporal patterns of the occupational placement?

The first finding is that predicted entry-level occupational placement of the US skilled immigrants varies widely by country of origin. Second, for the majority of countries there is evidence of improvement in the occupational placement over a decade. Third, placements by country of origin are convergent: individuals from countries with lower predicted entry-level performance progress faster than individuals from countries with higher predicted performance at arrival. Fourth, the convergence loses intensity over time: the growth rate experienced by a cohort within the first ten years weakens over the following decade. Fifth, countries lower placed initially do not fully catch up within ten years to those already at an advantage immediately after arrival in the US. The sixth finding is that country specific attributes impact on the improvement in immigrants' occupational placement mainly through their effect on initial performance: thus, they lose significance when initial occupational levels are added to the regressions.

The foremost reason for assessing immigrants' performance by using occupational placements instead of earnings is because the former are less likely to vary by city or state within the US compared to the latter. This is a significant methodological advantage when capturing performance of immigrants spread throughout the country. In addition, occupations are less likely to be affected by changes in the labor market conditions over time. Consequently, the period effect biases which have to be addressed when focusing on earnings are less of a problem if employing occupational placement as a measure of performance.

The analysis of immigrants' occupational placement lies in a cone of shadow when compared to the generous number of studies using earnings to evaluate performance. Nevertheless, researchers are becoming increasingly aware of the particular importance that

[1] Chiswick (1978)
[2] Borjas (1985), Lubotsky (2007), Kim (2009)

knowledge of occupational status has in understanding the structural economic and social shifts experienced by migrants. As of recent, discussions about the occupational placement of migrants have also become of more general interest. In the US, there is plenty of anecdotal evidence linked to both real life examples and media coverage about skilled immigrants employed in low skilled jobs, and about concentration of individuals from a particular country into one category of professions. Research focusing on occupational mobility of immigrants could provide rigorous grounds for such observations. More explicitly, since occupational choices are linked to the education level, the analysis of occupational placement may reveal how migrants' skills are utilized in their destination countries in comparison to where the nominal degrees suggest those migrants should be. Such a topic could potentially open a door for addressing issues related to global creation and allocation of human capital (Mattoo et al. 2008).

The magnitude and pattern of return migration can significantly bias the results in this paper. Although prior literature acknowledged this problem and some researchers made inferences about the nature of the selectivity, the bias stemming from out-migration is typically left unresolved in studies that rely exclusively on census data. I evaluate to what extent attrition of cohort size due to return migration affects the samples by country. I conclude that estimates are not significantly affected by patterns in return migration.

Furthermore, working with data from several Censuses raises serious methodological concerns because the samples are based on responses of different individuals. To check whether results change significantly when correcting for the potential biases, I rerun the individual-level regressions using pseudo-panel techniques. The patterns are robust to the methodological change.

The next section reviews the literature on the performance of US male migrants and its determinants. Section 3 focuses on the dynamic analysis of the occupational placement over time using census data. It includes four sub-sections: the first introduces the empirical strategy; the second describes the data; the third presents the results; and the fourth is dedicated to robustness checks. Section 4 focuses on conditional convergence, while the impact of country attributes on the occupational performance is evaluated in section 5. Both sections 4 and 5 are divided into two sub-sections, one presenting the empirical framework and the other describing the results. Section 6 summarizes the findings and talks about their policy implications.

2. LITERATURE REVIEW

Since the 1940s, the US has been confronted with increasingly large waves of inward migration, which, by the 1990s, had became equivalent in magnitude to the ones taking place around the beginning of the century, i.e. in the period of the First Great Migration. Borjas (1994) provides a succinct description of the so-called Second Great Migration including information about the historical context, the structure of immigrant flows by country of origin, and the most salient measures taken by the US immigration regulators in order to shape migration according to their policy objectives.

A wide scale phenomenon influenced by complex factors and having equally complex implications, the US immigration story became the topic of a very rich economic literature attempting to answer the endless list of questions posed by migration researchers. In what follows I will focus on the part related to the performance of male immigrants[3] and the determinants of their performance. Extensive surveys of the existing literature are available in Borjas (1994) and LaLonde and Topel (1997).

The research focusing on immigrants' assimilation is an arena of strong debates. One explanation for the lack of consensus on many topics in the literature can be found in the quality of data. No single source provides comprehensive information on immigrants, therefore authors compensate by imposing various assumptions and implementing different methodologies which often lead to conclusions that significantly differ from each other. The US Census, although most widely used[4] because of the richness in information, fails to distinguish between legal and illegal immigrants, doesn't account for return migration, and formulates questions essential for migration research ambiguously. To benefit from yearly flows of data, some authors use instead the Current Population Survey (CPS), while warning readers about the little reliability of their small sample-based estimates.[5] Alternatively, Immigration and Naturalization Service statistics are more accurate with respect to indicators of legal status, but fail to provide a clear picture of the individual ones, such as immigrants' income.[6] Longitudinal studies, although most conducive to comprehensive research, have often a restricted coverage,[7] so their conclusions are hard to generalize. To increase estimates' accuracy, other researchers combine data from various cross-

[3] Typically, migration studies tend to cover either men or women. This is due to the fact that analyses of female migration require the additional consideration of the specific selection bias arising from women's decision to participate on the labor market. Methodological differences aside, female migration research, although more restraint than research on men migration follows a parallel trajectory both in a temporal sense and with respect to the empirical strategy (Ex. Long (1980) applies for women migration the approach in Chiswick (1978), Schoeni (1997) and Schoeni (1998) follow similar strategies, the first paper with respect to men immigrants, and the second with respect to female immigrants).
[4] Chiswich (1978), Borjas (1985, 1987, 1994, 1995), Lalonde and Topel (1990), Duleep and Regets (1994) to name just very few who relied on census data.
[5] Funkhouser and Trejo (1995)
[6] Jasso and Rosenzweig (1986), Chiswick (1986) Jasso et al (2000)
[7] For example, focus on one type of occupation, as in Borjas (1989).

section and/or longitudinal sources.[8] The scarcest data sources, but very helpful in clarifying migrant self-selection issues, are those that identify information about US immigrants in their origin country.[9]

Economists use either earnings or occupational placement to proxy performance, i.e. the way immigrants deal with the complex and time consuming process of adapting to the host country's environment. While focus on occupational placement increased over time, most studies evaluating and explaining migrants' performance in the destination countries rely on earnings as a measure of performance.

The leitmotiv of discussions about immigrants' performance is the concept of "assimilation" i.e. the impact of time spent on the US labor market, other factors being constant. The evaluation of "assimilation" involves two approaches: assessing how migrants perform at a certain point in time after migration versus their performance around the time of arrival; and assessing how the pattern of migrants' performance over time relates to that of natives.

IDENTIFICATION OF ASSIMILATION PATTERNS

Immediately after arrival in the US, and keeping individual characteristics such as age, education, race etc. constant, migrants are shown to earn less than natives. This finding was interpreted using the human capital model (Ben-Porath, 1967) as a consequence of the absence or poor transferability of specific skills valued on the US labor market. The initial human capital investment necessary to acquire some of these skills depresses wages even further. As migrants overcome their disadvantages relative to natives, earnings start to grow, mirroring what literature refers to as "the skill transferability" mechanism, first described by Chiswick (1978).

Using multivariate analysis on data from the US Census 1970, Chiswick (1978) predicted that, because migrants are positively self-selected from their countries of origin with respect to ability and motivation[10], their earnings' growth actually exceeds that of natives, a situation which makes it possible for immigrants' earnings to equal and eventually overcome natives' earnings within 10 to 15 years since arrival. Chiswick's 1978 article inspired a significant number of subsequent studies, which confirmed its results in different empirical settings.[11] A challenge to this line of research came in 1985 when Borjas showed that cross-section analyses of migrants'

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[8] Hu (2000) uses the Health and Retirement Study (HRS) linked to the Social Security Earning data, while Lubotsky (2007) combines Current Population Survey (CPS) and the Survey of Income and Program Participation (SIPP).
[9] McKenzie and Rapoport (2007)
[10] Unless "push" factors, such as political conflicts, weaken or reverse the positive selection implied by the theory.
[11] Carliner (1980), DeFreitas (1980), Long (1980), Bojas (1982), Borjas and Tienda (1985)

earnings growth can be misleading due to presence of "cohort effects" in the assimilation estimates. Following "synthetic cohorts" - i.e. sets of individuals who immigrated during a certain period - through the US Censuses 1970 and 1980[12], Borjas found that the unobservable part in the quality of successive US immigrant cohorts[13], measuring precisely the ability and motivation - not related to education - that supposedly help migrants' earnings grow faster than natives', has steadily declined over time.

Borjas's results of lower assimilation compared to estimates produced by cross-section studies were restated in Borjas (1995) following addition of US Census 1990 to the analysis. Borjas (1989) and Funkhouser and Trejo (1995) confirmed presence of positive cohort effects for US immigrants using longitudinal survey and Current Population Survey (CPS), respectively, instead of US Census data. Implementing Borjas's synthetic cohort approach, Baker and Benjamin (1994) also provided evidence of decline in the unobservable quality for immigrants to Canada. Nevertheless, despite the general perception of both lower nominal entry earnings and larger education gaps relative to natives for the US 1970s and 1980s immigrant cohorts, a significant part of the literature could not reach conclusive evidence of a decline in the "unobserved" cohort quality even when using the same methodology introduced by Borjas (1985). Thus, Chiswick (1986) detects no significant cohort differentials in the unmeasured dimensions of productivity - such as language fluency, the quality of schooling and experience, and ability – although the study confirms that recent US immigrants are indeed less favorably selected on the basis of their level of schooling. Using Social Security Administration longitudinal data, Duleep and Dowhan (2002) find that immigrants' wages are lower at arrival, but then reach and even exceed those of natives, result which is in line with the optimistic depiction of migrants' trajectory in Chiswick (1978). LaLonde and Topel (1990) use data from Censuses 1970 and 1980, as well as Borjas's "synthetic cohort" approach amended by several methodological changes and show that, within the immigrant groups studied[14], assimilation estimates resemble the ones predicted by the "cross-section" studies, and that there is no evidence of a significant decline in cohort quality (measured as unobservable skills) over time. LaLonde and Topel motivate the difference in findings compared to Borjas (1985) based on the choice of

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[12] Composition of a synthetic cohort is not directly comparable across censuses because individuals surveyed for one census are not necessarily the ones selected to fill out the questionnaires for the subsequent censuses. However, they refer to the same population, which nevertheless changes over time due to natural causes as well as out-migration.
[13] Proxied by relative entry earnings of migrants relative to natives while keeping constant the impact of other determinants of entry earnings (age, education etc).
[14] Europe, Canada, Australia; East and South Asia; Middle East; Mexico; Latin America

the reference group used to correct for the so-called "period effects," which refer to the impact on earnings of changes in the general conditions of the US labor market over a decade. Assuming that overall economic circumstances affect immigrants and natives in similar ways at the same point in time, period effects can be taken care of by evaluating immigrants' performance *relative* to the performance of a reference group, usually composed of natives. As an illustration of how the choice of the reference group differs in the literature, while Borjas (1987) uses earnings of a fixed cohort – persons who migrated before 1950 – to normalize earnings in the census years 1970 and 1980, LaLonde and Topel (1990) recommend that wage growth of immigrants be normalized by wage growth of immigrants of the same ethnicity who have been in the US for more than 30 years or of ethnically similar natives.[15]

Duleep and Regets (1994) open a new debate related to cohort effects by claiming that research showing sluggish growth rate of US male immigrants' versus natives' earnings makes an incorrect assumption according to which different US immigrant cohorts experience the same growth in earnings. Duleep and Regets suggest, that in reality the earnings growth rates differ by cohort and are inversely related to entry earnings: the lower the entry earnings the higher the earnings growth rate, therefore the more likely the convergence between immigrants' and natives' performance levels. In the authors' opinion, Borjas's belief that entry earnings proxy reasonably well the cohort quality is a false premise to start with, because entry earnings hide unobservable skills, not immediately valued in the US labor market but useful for the acquisition of US skills. Otherwise stated, the low initial earnings of immigrants arriving in recent cohorts may be due to more intensive human-capital investment, which will lead to higher earnings later in life. As a continuation of this argument, Duleep and Regets (1997, 1999) design a Immigrants Human – Capital Investment (IHCI) model, the thesis and central finding of which is that, conditional upon education and age, immigrant entry earnings and earnings growth are inversely related. In response to criticism from Duleep and Regets (1994), Borjas (2000) relaxes the constraint of constant growth in immigrant's earnings by cohort and evaluates whether the rate of wage convergence exhibits cohort effects, i.e. whether most recent immigrant cohorts experience faster or slower wage growth compared to earlier ones. His analysis of US Censuses 1970, 1980 and 1990, indicates presence of conditional convergence in the immigrant population, in the sense that the wages of immigrants having the same initial level of human capital converge over time. However, this finding is not robust to simple attempts to control for the bias introduced by

[15] Other studies that have shown particular interest in addressing the period effects bias are Baker and Benjamin (1994) and Bloom and Gunderson (1991) both of which focus on the immigrants to Canada.

measurement error. In line with Duleep and Regets (1994), Hu (2000) detects strong immigrant earnings convergence: those who start at lower earnings quickly make up a large part of the deficit relative to other immigrants.

A recent generation of studies relies on combinations of cross-section and longitudinal sources rather than the widely used repeated cross-section data to produce assimilation estimates that control for biases caused by individual heterogeneity and out-migration. The findings of these studies differ significantly from previous results by depicting a more pessimistic outlook of assimilation. Thus, Lubotsky (2007) finds previous studies to have overestimated the wage progress of immigrants who arrived between 1960 and 1980. Nevertheless, the extent of the "cohort effect" is also shown to have been exaggerated. Focusing on period 1994-2004, Kim (2009a) obtains little evidence of convergence between earnings of immigrants and natives, both at aggregate level, and by migrants' country of origin.

IMPACT OF COUNTRY OF ORIGIN EFFECTS ON ASSIMILATION PATTERNS

Most researchers find significant differences in immigrants' performance patterns among broadly defined ethnic or geographic groups. In other words, the assimilation effect, i.e. the impact of the number of years spent by migrants' on the US labor market on performance is shown to vary by migrants' origin. Thus, the effect on earnings of time in the United States, holding total labor market experience constant, is weaker for immigrants from countries that more closely resemble the United States (Chiswick, 1978). Consequently, migrants from Canada and the Western Europe tend to have higher earnings relative to those from other areas (Chiswick, 1986, Borjas, 1987). On the other hand, earnings in the US of Mexican migrants are lower compared to earnings of natives or immigrants belonging to other ethnic groups, a characteristic also inherited by second-generation Mexican immigrants (Chiswick, 1977, 1978). Borjas (1995) and Duleep and Regets (1997) indicate sizable differences in the rate of wage growth experienced by different national origin groups in the United States. In an effort to capture more accurately the ethnic specificity of the assimilation patterns, Schoeni (1997) focuses on the variation in assimilation patterns of US male immigrants by specific countries of origin as opposed to broadly defined groups. Comparing three US Censuses, 1970, 1980 and 1990, he finds evidence of significant unexplained variation of assimilation rate across birth countries which he attributes to changes in the US wage structure, cultural differences, discrimination, the illegal status of some workers and English language abilities. Borjas (2000) investigates the extent of earnings' convergence by country of origin. Friedberg (2000) uses cross-section data for Israel and finds that human capital is imperfectly portable across countries of origin, so that migrants from some countries are able to perform better than migrants with similar qualifications but from other countries.

Literature has identified country of origin characteristics and US immigration policy as important determinants of both immigrants' initial performance and subsequent growth. Such findings are intuitively motivated by the impact of these factors on the selection of individuals who decide, and pursue the decision, to migrate to the United States. Country of origin attributes are shown to further shape the stock of immigrants in the US by influencing return migration decisions. Jasso and Rosenzweig (1986), the first to include country specific attributes in regressions explaining migrants' earnings, show that almost all named country-of-origin differences in naturalization rates and in performance are eliminated when differences in country characteristics influencing migration and re-migration decisions are taken into account. Borjas (1987) identifies channels through which migrants to the US select themselves from the distributions of the origin country populations. Provided that correlation between skills in the country of origin and US is sufficiently high[16], if the country of origin has relatively less dispersion in its earnings distribution than the US, migrants will be positively selected, and, conversely, if the earnings distribution is more dispersed in the country of origin relative to the US, migrants will be negatively selected.[17] Borjas tests his selection model for 41 countries of origin, using regressions of estimated immigrant-native entry wage differential, assimilation rate, and emigration rate (out of origin country into the US) on indicators specific to those countries. Borjas (2000) also models the extent to which country of origin attributes impact on immigrants' earnings levels and growth. Mattoo et al. (2000) find both country specific attributes and US immigration policy measures to be powerful explanatory factors determining the initial occupational placement of immigrants.

The widely documented decline in US immigrant cohort overall quality levels has been overwhelmingly attributed by researchers to the historical changes in the national country of origin mix. The latter are considered to have occurred due to the selection forces activated by changes in the US immigration policy on one hand, and developments in countries of origin on the other (Chiswick, 1986, Borjas, 1992). Initially the largest share of US migrants came from the Western Europe and Canada. Over time, and especially since the 1960s, several Asian and Latin American countries took the lead as the most important sources of migrants. Because of the

[16] condition which ensures portability of skills across countries

[17] Situations with negative or low correlation between skills in the country of origin and the US are "refugee sorting" cases, such as those where source countries experience communist takeovers. Their applicable selection prediction could be for immigrants with below-average earnings in the source country to be placed in the upper tail of the earnings distribution of the host country.

lower schooling attainment of populations in these countries compared to Western Europe, Canada and the US, the overall quality (measured as education and wage gap to natives) of the typical US immigrant has declined. The US immigration policy instruments considered to have contributed to the change in national mix are the removal of the national-origin quota system and the high importance given since 1965 to family-related preferences for admitting immigrants. Using Immigration and Naturalization Service data, Jasso et al. (2000) find a reversed trend in US immigrants' quality especially since the 1980s, change attributed primarily to recent developments in the US immigration policy geared towards giving more priority to highly educated immigrants.

THE OUT-MIGRATION SELECTION BIAS

A topic that has received attention in the literature, but was insufficiently explored due to data concerns is the selection bias imposed by return migration. Most studies estimate assimilation based on US Censuses, which unfortunately do not allow control for the impact of out-migration. One solution to this problem would be to rely on longitudinal and immigration data instead. At least in the early years, these sources lacked the degree of detail and the level of coverage available in the census data, caveats rendering them much less useful for implementing econometric models that explain immigrants' performance. However, recent research based on longitudinal data has proven more successful in estimating assimilation while controlling for return migration.

Among the studies that attempted to evaluate the magnitude of return migration, frequently cited ones are Warren and Peck (1980) and Warren and Kraly (1985) which estimate that 30 per cent of the foreign-born US residents leave the country within a decade or two after arrival. In addition, Jasso and Rosenzweig (1982) calculate as of January 1979 a cumulative net emigration rate of 50 per cent for the 1971 cohort of legal US immigrants, by country and area of origin. With respect to out-migration selectivity, one of the findings of Borjas's 1989 longitudinal study focusing on scientists and engineers states that people with worst performance are more likely to emigrate out of the US. Relying on longitudinal data as well, Hu (2000) and Lubotsky (2007) also show that US out-migration is negatively selected. On the other hand, Jasso and Rosenzweig (1988) infer, using data from the Immigration and Naturalization Service (INS), that the most skilled workers are also the most likely to become out-migrants. Using both US Census 1980 and Immigration and Naturalization Service (INS) data, Borjas and Bratsberg (1996) estimate for 70 countries the out-migration rates as of 1980 for migrant flows who arrived during the 1970s and conclude that immigrants tend to return to wealthy countries which are not too distant from the United States and that the return migration process accentuates the type of selection of immigrants out of their origin countries, described by Borjas in his 1987 study. More specifically, of those who come from countries having originally sent positively selected migrants to US, it is the "worst of the best" that leave while the out-migrants originating from countries characterized by negative selection vis-à-vis the US are the "best of the worst." Using the longitudinal component of the Current Population Survey (CPS) [18] and a methodology described in Kim (2009b), Kim (2009a) finds that the extent of return migration is small and its impact on assimilation not significant.

OCCUPATIONAL PLACEMENT AS A PROXY FOR PERFORMANCE

While the majority of US migrant assimilation studies focus on earnings, there have been attempts in the literature to account for patterns in occupational assimilation and mobility. Chiswick (1977) brings one of the first contributions to this area. Jasso and Rosenzweig (1986, 1988) use occupational indicators in addition to earnings to assess immigrants' performance. Green (1999) employs 1981, 1986 and 1991 censuses to show that after a period of adjustment lasting for about three years since migration, Canadian immigrants are more likely to be found in professional and more skilled manufacturing occupations compared to natives, an advantage due to the nature of the Canadian immigration policy, but found to decline across successive cohorts. Canadian immigrants are more occupationally mobile even long after arrival, compared to those who are not assessed based on their skills at entry into Canada or who lack initial language fluency. Using 2000 US Census data, Mattoo et al. (2008) analyze to what extent skilled migrants from various countries are employed in unskilled jobs on the US labor market. The study finds evidence of significant variation in immigrants' occupational placement by countries of origin which persists even after accounting for education and experience accumulated in the US. However, a large part of the variation is explained by country of origin attributes affecting the quality of human capital on one hand, and by US immigration policy affecting selection of migrants on the other. Therefore, the authors conclude that the "underplaced" immigrants suffer primarily from low (or poorly transferable) skill levels rather than skill underutilization. Chiswick et al. (2005) design and test on Australian longitudinal data a model of immigrants' occupational mobility. The model predicts that occupational mobility from the last job in the country of origin to the first and then the subsequent ones in the destination countries follows a U shape, the depth of which depends on the similarity between origin and destination countries, but also on migrants' skill levels. The decline in occupational status from the last job in the country of origin to the first job at destination mirrors lack or poorly transferable skills. As these skills

[18] The CPS Merged Outgoing Rotation Group

earn recognition on the US labor market, occupational status improves. There is an inverse relationship between the initial decline in skills and the subsequent recovery, proportional to the investment in human capital undertaken by the migrant in the destination country. Immigrants from countries very similar to the destination may experience little or no downward mobility, and hence little subsequent increase. In addition, immigrants without skills or with poor ones are also not likely to make large investments into skills upon arrival; for them too, the model predicts little or no subsequent increase.

My study focuses on occupational placement as an indicator of performance. It evaluates assimilation patterns using the "synthetic cohort" approach introduced by Borjas (1985) for earnings and implemented by Green (1999) for occupational choice. By using country of origin attributes to explain performance, the study draws on the conclusions of the occupational placement analysis by Mattoo et al. (2008), but also relates to Borjas (1987, 2000) and Jasso and Rosenzweig (1986) who focus on earnings. I evaluate the convergence in immigrants' occupational placement by country, employing a model which has also been used by Borjas (2000) for earnings. Finally, my results of negative correlation between entry levels of occupational placement and improvements in occupational placement over time and by country when controlling for human capital characteristics relate to work by Borjas (2000), Duleep and Regets (1997) and Hu (2000).

3. DYNAMIC PATTERNS IN OCCUPATIONAL PLACEMENT OF US SKILLED MIGRANTS BY COUNTRY OF ORIGIN

3.1. EMPIRICAL FRAMEWORK

The study uses the "synthetic cohort" approach introduced by Borjas (1985) to evaluate assimilation in the sense of progress made by US immigrants over time relative to their initial position on the US labor market. Performance is measured by occupational placement (OP). I employ OLS with country fixed effects to explain the *OP*[19] as of Census year *t* for migrant *i* who came to the US in decade *d* (equation 1). Decades are assimilated to cohorts in the sense used by Borjas (1985).[20] The implicit assumption is that migrants arriving within a decade are homogeneous with respect to ability. *OP* is measured using three alternative variables, one

[19] in log specification
[20] Therefore the two terms are used interchangeably throughout the paper.

indicating the prestige level, and the other two the educational content of each occupational category.

The dependent variable is regressed on several human capital indicators, which are: general work experience (proxied by age and age squared), years since arrival or since migration (represented by a dummy variable indicating whether migration took place in the first or the second half of the decade),[21] and level of education (captured by the six dummy variables grouping the years of education in: less than five, five to nine, ten to twelve, high-school level, some college, Bachelor's Degree or higher).

To account for the age-at-migration bias (Friedberg, 1992), the estimation samples include only migrants who earned their degrees before migration. Additionally, age restrictions insure cohort comparability across censuses.[22] Regressions for each of the three OP indices are weighted and run separately by census year *t* (where *t*=1980, 1990 or 2000) and decade of arrival *d* (where *d* = 1970-1979 or 1980-1989). Altogether, this implies 15 estimations, i.e. 18 (three dependent variables * three Censuses * two decades) minus three, since Census 1980 only captures the 1970s decade.

$$\begin{aligned}\ln OP_{idt} &= \alpha_{dt} + \beta_{1dt} AGE_{idt} + \beta_{2dt} AGE_{idt}^2 + \beta_{3dt} YRS\_IN\_USA\_DUMMY_{idt} + \\ &\sum_{\upsilon=1}^{6} \beta_{4dt\upsilon} EDUC\_DUMMY_{idt\upsilon} + \sum_{\tau=1}^{122} \beta_{5dt\tau} CTRY\_DUMMY_{idt\tau} + \varepsilon_{idt}\end{aligned} \tag{1}$$

The specification is related to the econometric models of wage determination previously used in the migration literature for estimating earnings assimilation. As claimed by Borjas (1995) and LaLonde and Topel (1990) there are three types of major biases that can affect the accuracy of assimilation estimates. These are: cohort effects, period effects and the return migration effect. Cohort effects refer to unobservable changes in the quality of cohorts entering the US at different times. Period effects reflect modification of labor market conditions from one census to another. To eliminate period effects, studies focusing on earnings measure assimilation of migrants relative to a comparison group expected to have been influenced similarly by the changes in the economy. A third source of bias is the non-random cohort attrition related to either mortality or return migration.

[21] Usage of intervals is justified by the fact that Census 1980 and Census 1990 do not provide the individual years of migration.
[22] For example, the youngest individual in the 1980s decade is 16 years old as of Census 1990, therefore the youngest individual who arrived in the 1980s is 26 years old as of Census 2000.

First, to account for the potential biases arising from cohort effects, I follow the progress of individuals in a particular cohort (identified by decade) through several censuses, so that the errors due to unobserved differences among cohorts (decades) cancel out. Second, since the paper focuses on cross-country comparisons, period effects should not be of significant concern if assumed that changes in labor market conditions affect all immigrants in the same way irrespective of where they come from. Provided that were not so, because one of the three variables used to proxy occupational placement is constant over time, the impact of period effects could be identified by checking whether the results based on that index differed significantly from the ones based on the other variables. Part of the third source of bias, namely the mortality rate, is dealt with by imposing upper limits on the ages of individuals. The more troublesome concerns about return migration are addressed in sub-section 3.4.1. That analysis consists of comparisons of cohort sizes over time and identification of the countries with the highest rate of attrition. Re-estimating the regressions after excluding problem countries leads to results not significantly different from the main ones.

To isolate the country effects on immigrants' performance, the strategy employed is to compare predicted occupational placement of individuals identical with respect to human capital endowments, but coming from different countries. This way, it is insured that all the variation in the compared levels of performance stems from the coefficients on country dummies, β_5. Thus, the aim of the 15 estimations based on equation (1) is to predict the occupational placement, $\hat{O}P = e^{predicted(\ln OP)}$ in 1980, 1990 and 2000 for hypothetical individuals with identical human-capital variables, who come from different countries, and are present in the US at the time of two or three censuses depending on when they migrated. Next, I calculate the predicted Occupational Placement Improvement $\Delta\hat{O}P_{i\tau,t-(t+10)} = \hat{O}P_{i\tau,t+10} - \hat{O}P_{i\tau,t}$ as the predicted change in the level of professional achievement of hypothetical individual i from country τ, between years t and t+10.

I construct two hypothetical individuals per country (Table 2), each with at least a Bachelor's Degree earned before migrating, and having arrived at 25 years old, one in 1975, and the other in 1985.[23] The 1975 migrant is assumed to be captured by all three censuses, the 1985 one only by the two most recent ones. The individual arriving in 1975 is 30 years old in 1980 (therefore 40 in 1990, and 50 in 2000), while the one arriving in 1985 is 30 years old in 1990 (and 40 in 2000).

[23] Because variable "years since migration" is identified by half decades, the 1975 and 1985 arrivals refer to intervals 1975-1979 and 1985-1989 respectively.

Finally, this analysis produces the following eight sets of predicted occupational placement indicators that will be used in section 3.2. to assess US skilled immigrants' performance over time and by country: (1)$\hat{O}P_{1980,\tau}$, $\hat{O}P_{1990,\tau}$, $\hat{O}P_{2000,\tau}$, $\Delta\hat{O}P_{1980\text{-}1990,\tau}$, $\Delta\hat{O}P_{1990\text{-}2000,\tau}$, for the hypothetical individual who arrived in the 1970s; (2) $\hat{O}P_{1990,\tau}$, $\hat{O}P_{2000,\tau}$, $\Delta\hat{O}P_{1990\text{-}2000,\tau}$, for the hypothetical individual who arrived in the 1980s. τ stands for country of origin and takes values from 1 to 122.

3.2. DESCRIPTION OF THE US CENSUS DATA

This paper relies on data from the 5% IPUMS samples of the US Censuses 1980, 1990 and 2000[24] and focuses on employed male immigrants, not living in "group quarters", not enrolled in school as of 1980, 1990 or 2000, and whose reported years of immigration lie within the 1970-1989 interval. The sample in Census 1980 is random, each observation representing 20 individuals in the US population, while Censuses 1990 and 2000 are weighted so that each observation represents a different number of individuals in the US. To increase the over time structural stability of cohorts, I focus only on people who earned their degrees in the origin country. Since a variable indicating the place where education was obtained is not directly available in either census, I construct it using the number of years of education and the age at migration. A person is considered "US educated" if he arrived in the US before he would have normally acquired their declared education level. For example, if a university graduate arrived at the age of 23 or older, then he is considered "foreign educated".

Censuses report occupation only for people aged 16 or more. When following the 1980s cohort through 1990 and 2000 I set the minimum age to 16 for Census 1990 and 26 for Census 2000, whereas when analyzing individuals arriving in the 1970s, whose performances can be captured by all three censuses, the minimum ages are defined as 16, 26 and 36 for Censuses 1980, 1990 and 2000, respectively. To reduce the effect of cohorts thinning out across censuses because of older individuals, I also place upper limits on the age intervals used in the samples: 40 for Census 1980, 50 for Census 1990 and 60 for Census 2000.

Summary statistics including size of cohorts, weighted and not-weighted, and information on sample structure by age, years since in the US and education are available in Table 2. The first three columns refer to the individuals who arrived in the US during the 1970s and whose performance levels are captured by Censuses 1970, 1980, 1990. Arrivals in the 1980s are summarized in columns 4 and 5. The first row indicates the size of the five samples, while the

[24] Available at ipums.org

second shows the equivalent in the whole US population. In principle, the numbers for each decade should decline across censuses due to return migration or mortality. Counter-intuitively, it can be observed that samples sometimes increase over time. For example, the 1980s arrivals counting 1,668,342 people in 1990, increase to 1,704,575 in 2000. The biggest increase in cohort size occurs between Census 1980 and Census 1990 for the 1970s arrivals (22,893 individuals). This may be due to measurement errors, including undercounting of illegal migrants and methodological differences across censuses, issues that will be detailed below. Despite the upward bias, the relative constancy in the shares of migrants by half-decade of arrival, as well as the stable proportion of the highly educated individuals (4+ years of college) across samples are positive signs that the data capture the same people over time.

As indicators of occupational placement, I employ three alternative variables. Two of them are available from the IPUMS samples and the third is based on own calculation. The first, labeled Prestige Index, does not vary by census, and measures the prestige associated with an occupation.[25] The second, labeled Education Index 1, indicates the educational content of each occupation and is based on the share of individuals with undergraduate and graduate degrees who declare an occupation.[26] Both the Prestige Index and Education Index 1 take values from 1 to 100. The last variable, labeled Education Index 2, indicates the educational content of an occupation and is calculated as the weighted average of the number of education years of all individuals, male and female, native and foreign-born alike, who declare an occupation. The two indices of educational content are sample-dependent; therefore they vary by census, unlike the prestige indicator, which is constant across periods. On the other hand, the Prestige index which is derived from individual answers to a survey might be more sensitive to modifications in the survey respondents' profile by country of origin. However, the fact that the Prestige index is correlated up to 90% with the two Education indices provides assurance that the potential bias is not significant. All three indices increase with the education level as can be seen from Table 3.

The study uses, in its first stage, 122 countries of origin for which data are available in all three Censuses. To ensure readability, only the 80 most important sending countries are displayed in graphs and used as basis for the regressions of predicted indices on country-specific variables. These 80 countries represent 95% of the male immigrants who were in the US as of

[25] Details regarding its content and calculation are available at http://usa.ipums.org/usa-action/variableDescription.do?mnemonic=PRENT
[26] Details about calculation and interpretation at http://usa.ipums.org/usa-action/variableDescription.do?mnemonic=EDSCOR90

Census 1990, and met the criteria by which I constructed this paper's dataset: employed, not living in group quarters, not in school, having entered the US in the 1970s or the 1980s.

The US Censuses are among the richest databases available. However, as I mentioned before, they have caveats. First, it is impossible to follow the exact same individual through several censuses. In addition, censuses do not identify the illegal immigrants and do not track return migration. Finally, throughout decades, there have been changes in methodology and coverage. Thus, the fact that the question asking for the year of immigration was reformulated between the last two censuses complicates the task of accurately isolating immigrants by cohort. The 1980 and 1990 questionnaires require that individuals report the year they came to stay, while the 2000 one asks for the year they came to live in the US, implying that for those having entered the country a multiple number of times, prior experience may pass unobserved. In addition, some individuals may declare the year of immigration as the year when they received their permanent residence, although they may have already spent time in the US as students, on work visas or as illegal migrants.[27]

Since censuses are filled out in spring, I assume the information gathered by Census 1990 about immigrants arriving in 1990 cannot fully mirror the degree of comprehensiveness available for that year as of Census 2000, therefore I choose to exclude the 1990 arrivals from the 2000 dataset. The same issue also arises with respect to Censuses 1980 and 1990. For the reasons detailed above I consider interval 1975-1980 reported by Census 1980 equivalent to 1975-1979 reported by Census 1990.

Censuses 1980 and 1990 report years of immigration as intervals, while Census 2000 reports the individual years. For the sake of consistency, I grouped the available data from all three sources into two decades, 1970-1979 and 1980-1989, each with two periods of arrival: 1970-1974 and 1975-1979 for the first; 1980-1984 and 1985-1989 for the second. The periods of arrival proxy time spent on the US labor market. For example, an individual who migrated during 1975-1979 is considered to have spent in the US between 1 and 5 years, counted as of Census 1980.

3.3. EMPIRICAL RESULTS

The coefficients based on the estimation of equation (1) with Education Index 1 as a dependent variable are provided in Table 4. Annex table A1 provides the results for the other two

[27] Jasso et al. (2000) claim that recent immigrants sampled in the decennial censuses "may be neither recent nor immigrant."

specifications. Assuming migrants arriving in the first and the second half of a decade are homogeneous with respect to ability, the coefficient for years since migration (β_3) provides the assimilation effect.[28] The assimilation effect is negative and significant in each specification. Since the dummy takes value 1 if an individual migrated in the second part of a decade, the negative sign indicates that, keeping other things constant, the more time migrant spends in the US, the higher the predicted level of performance. Thus, in accordance to previous literature, experience acquired on the US labor market is an important determinant of performance. The estimations show a different picture for the general work experience, measured by age and its quadratic: these variables are only significant for the 1985 arrival. The small magnitude of the coefficients and standard errors is due to the log specification of the occupation indices. Mirroring Table 3 from sub-section 3.2, the coefficients of the education dummies suggest that the higher the educational level, the higher the occupational placement index.

Figure 1 presents the 1990 ÔP by country for the hypothetical individual arriving in the US in 1985. The results suggest that entry level occupational placement of skilled male US immigrants varies greatly by country of origin. The highest level of performance is attained by migrants from developed countries while the lowest indices are prevalent among those from Latin American countries.[29] These patterns confirm Mattoo et al. (2008) which also find that country of origin attributes and selectivity factors explain a lot of the surprisingly wide heterogeneity in performance of individuals with the same nominal education levels.

To evaluate the progress within the ten years closest to migration, I plot ΔÔP between year 2000 and year 1990 versus the ÔP in 1990 for the 1980s arrival, as shown in Figure 2, and ΔÔP between year 1990 and year 1980 versus the ÔP in 1980, for the 1970s arrival in Figure 3a. The distribution of countries based on ÔP, which is represented on the X axis, depicts a more complete version of the picture presented in Figure 1 for selected countries and one period of arrival. Figures 2 and 3a show that there is improvement in the occupational placement within the decade closest to the arrival time, for skilled immigrants coming from various countries. Additionally, the negative correlation between the entry levels of occupational placement and the subsequent improvement seems to suggest the existence of convergence forces working to reduce the differences in performance levels among various countries. These patterns are robust to

[28] If there is difference in immigrants' ability between the two periods of arrival within a particular decade, then β_3 captures cohort effects rather than assimilation. In that case, the assimilation effect itself can not be identified at all because the 1980 and 1990 censuses do not provide information on the specific years of arrival.
[29] For comparison, as of Census 1990, the weighted average occupational index calculated for all US-born skilled males (irrespective of wage or employment status) is about 77.

alternative definitions of occupational placement, as illustrated by Figures A1 a and b, and A2 a and b.

To assess whether the strength of the negative correlation survives over time, panels a and b of Figure 3 plot the performance of the 1970s arrival over 20 years since migration. The first panel shows the progress during the 1980s versus initial occupational placement in 1980, while the second plots the performance improvement during the 1990s versus the level in 1990. The convergence continues in the second decade since arrival, but at a reduced rate. Results are robust to using the alternative indices of occupational placement (Figures A1 b and c and A2 b and c).

The question naturally arising is whether the convergence suggested by the data leads to full catch-up of countries experiencing low initial performances to the level of countries that started higher up. As Figure 4 reveals, catch-up is not likely to occur within the first ten years since arrival for either the 1985 or the 1975 immigrants. Figure A3 shows the same patterns for the 1985 arrival using alternative measures of occupational placement.

3.4. EXAMINATION OF MAJOR SOURCES OF BIAS

The findings of the previous section may reflect a distorted picture of the real trends in immigrants' occupational placement if there are factors that systematically and unilaterally impact on the composition of cohorts across censuses. This section aims at quantifying the effect of two important sources of bias: out-migration and usage of repeated cross-section datasets.

3.4.1. Out-migration

Many studies have shown that out-migration is selective.[30] Thus, the set of individuals who decide to return to their countries of origin or leave the US for other destinations is not a random sample from the initial distribution of the migrants. If the most (least) able members of a cohort out-migrate, the improvement in occupational placement across the decade is understated (overstated). A differential selective effect of return migration by country of origin may cast serious doubts on the validity of the results obtained hitherto in the paper.

The US censuses cannot provide a clear picture of return migration, mainly because different individuals are surveyed in different years.[31] In addition, cohort sizes are also affected

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[30] Jasso and Rosenzweig (1988), Borjas (1989) , Borjas and Bratsberg (1996), Hu (2000), Lubotsky (2007)

[31] All the detailed information available in the census databases comes from the answers to the long-form questionnaires, which are filled out by one in six persons residing in the US. The sample changes from census to census, making it impossible to track the same individuals over time.

by factors related to measurement errors and methodological differences, which add to the difficulties of isolating the same cohort in several consecutive censuses. The burdens accentuate as research moves from general to specific interests in attempt to capture the characteristics of a specific set of migrants. Table 2 in sub-section 3.2 provides examples of counterintuitive increases in cohort sizes. Normally, these should decline over time due to return migration and natural causes.

Previous studies relying on US census data make inferences about the selective nature of return migration, but do not incorporate it explicitly in estimations of assimilation.[32] For this purpose, researchers typically turned to alternative data sources, as described in section 2.

The approach taken in this paper is a very simple one and consists of calculating the rate of attrition for the skilled immigrants in a particular cohort over the decade that is closest to their arrival in the US. As the next step, the countries with the highest rates of return migration are identified and excluded them from the samples. Finally I re-estimate equation (1) and plot the predicted variables as described in sub-section 3.3. [33]

To illustrate, I will focus on the case where the occupational placement improvement, defined as Education Index 1, is evaluated for the 1985-1989 arrivals. The ranking of countries by the rate of change in the number of skilled members of the 1985-1989 period of arrival leads to the identification of several mostly developed states[34] which seem to have experienced the highest levels of out-migration during 1990 and 2000. As shown in Figure 5, the relationship between the predicted occupational placements obtained after eliminating those countries from the sample is similar to what was presented in Figure 2 of sub-section 3.3. The conclusion that results do not change after eliminating countries with significant out-migration incidence is robust to using alternative cohorts and definitions of the occupational placement index.

3.4.2. Pseudo-Panel Analysis: Biases Due to Using Repeated Cross-Section Datasets

As explained before, the sample of people responding to the long-form questionnaires of the US Censuses is drawn anew each decade from the entire population of the country. Hence, the validity of the inferences stated in this paper may be affected by the comparison of different

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[32] Duleep and Regets (1997) take a step in the right direction by suggesting a method for testing the sensitivity of results to biases caused by sampling error and migration.
[33] The dependent variables are not logged prior to estimating the equations. There is no significant difference between results based on a log-functional form as opposed to original variables. The log specification was primarily introduced to facilitate the convergence analysis.
[34] Australia, Belgium, Brazil, Canada, Chile, France, Germany, Israel, Japan, Mexico, Netherlands, New Zealand, Sweden, Turkey, United Kingdom.

sets of individuals over time. Because availability of real panel data is typically more problematic than that of repeated cross-section datasets, researchers have determined the conditions under which the latter can produce unbiased estimates equivalent to the ones based on estimating genuine panels. The so-called pseudo-panel methodology, in which repeated cross-sections are treated as panels was introduced by Deaton (1985) and consists of estimating economic relationships based on cohort means rather than individual observations. This approach is based on the assumption that the cohort population means are genuine panels in that, at the population level, the groups contain the same individuals over time.

Equation 9 estimates a pooled set of T independent cross-sections:

$$y_{i(t)t} = x_{i(t)t}\beta + \theta_{i(t)} + \varepsilon_{i(t)t} \quad i(t)=1,\ldots N, \text{ and } t=1,\ldots.T. \qquad (9)$$

Individuals are indexed by *i(t)* to make it clear that each database is composed of different people. The individual effects $\theta_{i(t)}$ are likely to be correlated with the explanatory variables in $x_{i(t)t}$. In a genuine panel this problem is solved by treating individual effects as fixed unknown parameters. Such an approach is not feasible with repeated cross-sections. Define C cohorts, each with a fixed membership that remains the same throughout the entire period of observation. Provided each individual observed in the survey belongs to exactly one cohort, the observations in each cohort can be averaged to yield equation 10 below:

$$\bar{y}_{ct} = \bar{x}_{ct}\beta + \bar{\theta}_{ct} + \bar{\varepsilon}_{ct} \quad c=1,\ldots.C, \text{ and } t=1,\ldots.T \qquad (10)$$

If the number of observations in each cohort is very large it can be assumed that $\bar{\theta}_{ct} = \bar{\theta}_c$, where $\bar{\theta}_c$ are cohort fixed effects. Consequently,

$$\bar{y}_{ct} = \bar{x}_{ct}\beta + \bar{\theta}_c + \bar{\varepsilon}_{ct} \quad (11)$$

Consistency of the β coefficient hinges on accounting for the measurement error that arises from the estimation of the unobserved population cohort means $\tilde{y}_{ct}$ using the sample-based average means $\bar{y}_{ct}$. Based on the findings in the literature (Deaton, 1985; Verbeek and Nijman, 1992), most applied researchers ignore the measurement error if the sample size of each cohort exceeds 100 individuals.

Returning to the assumption that $\bar{\theta}_{ct} = \bar{\theta}_c$, the successful usage of pseudo-panel techniques requires that the average characteristics of individuals do not differ over time (across cross-sections). For the specific case of my paper, there are two reasons to doubt the validity of this assumption.

First, migrants could move from a cell to another by acquiring more education. Thus, a high-school graduate in 1980 might obtain a Bachelor's degree by 1990. To prevent this, my samples are composed only of individuals who have obtained their degrees before coming to the US. For example, if the age-at-arrival in the US is more than 18 years old and the individual has a high-school degree I assume he has earned it before migration and exclude him from the dataset.[35]

Second, if different countries have different return migration or death rates the conditions needed for consistency of pseudo-panel estimates do not hold. That is, the average characteristics of those observed in 1980 might differ from those observed in 1990 and 2000. Attrition due to natural causes is addressed by setting upper limits on ages of migrants included in the samples. With respect to return migration, sub-section 3.4.1 found that it does not change the main results of the paper in a significant way. Therefore I will assume that the potential of return migration to weaken the validity of the pseudo-panel estimators is minimal. Consequently, I will proceed with implementing the techniques described above in order to account for the biases related to treating repeated cross-sections as regular panels.

I focus on the 1975 arrivals, and use Education Index 1 as a measure of occupational placement. I construct cohorts (in the sense implied by the pseudo-panel theory) by country, period of arrival (1975-1979; 1985-1989), and education level (unskilled; medium skilled and highly skilled). To minimize measurement errors, I delete from the sample those cohorts which include less than 100 individuals. In the end, the pseudo-panel dataset is left with 916 cells. Next, I average the Education Index 1, as dependent variable, and age with its quadratic equivalent, as explanatory variables, by cohort for each cross section (t=1980, 1990, 2000) in order to obtain a specification similar to the one suggested by equation 11. The model is estimated using fixed effects composed of three sets of dummy variables: for period of arrival, for education level, and for country interacted with census year. Figure 6 charts the occupational placement predicted based on the pseudo-panel estimations. The findings in the sub-section 3.3 seem robust to the change in methodology.[36] The same conclusion is reached by using alternative measures of occupational placement and the 1985 arrival.

4. CONDITIONAL CONVERGENCE

[35] The situation is a bit complicated for highly skilled migrants, because Censuses 1980 and 1990 do not allow identification of individuals with Bachelor's degree, Masters' degree, Professional degree or PhD. Using the same age-at-arrival benchmark may lead to some inaccuracies in estimating the place where education was obtained.

[36] As a robustness check, the analysis was repeated on samples that exclude origin countries identified by the previous section as having significant out-migration flows. Results revealed no significant changes in the assimilation patterns. They are available from the author upon request.

4.1. EMPIRICAL FRAMEWORK

Several recent contributions to the literature focusing on earnings have attempted to evaluate whether immigrants' wages converge over time. Duleep and Regets (1997) detected significant negative correlation between the initial earnings and earnings' growth when controlling for the education level of migrants. Conditional on similar initial human capital endowments, Borjas (2000) finds similar results, although not robust to simple attempts to control for the measurement error bias. Inversely, when human capital variables are not accounted for, Borjas obtains a positive, but weak correlation between wages and their growth. Like Duleep and Regets (1997), Hu (2000) provides evidence of significant conditional convergence. He also finds that convergence is present even when not controlling for education and other human capital indicators, but that, as Borjas (2000) showed, it is weaker than the conditional convergence.

This section tests for convergence in the patterns of occupational placement among countries, provided that immigrants' individual characteristics, such as age, education, and period of arrival are kept constant.[37] The analysis relies on the predicted performance indicators inferred using the methodology of sub-section 3.1 for the two sets of hypothetical individuals described in Table 1. I evaluate the strength of the relationship between the rate of growth in occupational placement and the initial occupational placement by estimating the models in equation 2 for the 1985 arrival, and 3, 4 and 5, for the 1975 arrival. In accordance with the predictions of classical β-convergence models[38] the θ coefficients conditional on human capital endowments are expected to be negative and significant.

$$(1/10)\Delta(\mathit{predicted}\ln OP_{1990-2000,\tau}) = \theta_1 * \mathit{predicted}(\ln OP_{1990,\tau}) + \eta_{1,\tau} \quad (2)$$

$$(1/10)\Delta(\mathit{predicted}\ln OP_{1980-1990,\tau}) = \theta_2 * \mathit{predicted}(\ln OP_{1980,\tau}) + \eta_{2,\tau} \quad (3)$$

$$(1/20)\Delta(\mathit{predicted}\ln OP_{1980-2000,\tau}) = \theta_3 * \mathit{predicted}(\ln OP_{1980,\tau}) + \eta_{3,\tau} \quad (4)$$

$$(1/10)\Delta(\mathit{predicted}\ln OP_{1990-2000,\tau}) = \theta_4 * \mathit{predicted}(\ln OP_{1990,\tau}) + \eta_{4,\tau} \quad (5),$$

where τ stands for country.

[37] Application of convergence techniques to discrete variables may be of concern. However, this concern is diminished by the fact that the three discrete indicators used to measure occupational placement are characterized by large variation. Each of them includes at least 250 values to account for more than 350 occupations reported by the US Census.

[38] Barro (1991), Barro (1997)

To account for the heteroscedasticity due to the sampling error, all regressions are weighted by a factor $(n_t^{-1} + n_{t+10}^{-1})^{-1}$ as described in Borjas (2000), where n_t is the number of skilled people by country and half-decade of arrival, in Census year *t*.

4.2. EMPIRICAL RESULTS

This section tests empirically the hypothesis of *β*-convergence advanced in sub-section 4.1. Table 5 presents the results from estimating the growth rate in occupational placement on the initial level of performance for the 1985 and 1975 arrivals. Columns 1 to 4 provide evidence of convergence as suggested by the negative and significant coefficients for the predicted log of OP in 1980 and 1990 respectively. This result holds for all the alternative specifications of the dependent variable.

5. OCCUPATIONAL PLACEMENT IMPROVEMENT AND COUNTRY OF ORIGIN ATTRIBUTES

5.1. EMPIRICAL FRAMEWORK

The third stage of the analysis is an exploration of the extent to which the predicted Occupational Placement Improvement is accounted for by country-of-origin specific factors. Previous literature focusing on earnings found country attributes to be significant determinants of both the entry wages and the growth rates (Jasso and Rosenzweig, 1986, Borjas, 1987, Borjas 2000). Mattoo et al. (2008) identified two types of country specific influences on the initial levels of occupational placement: quality-related, explaining why nominally identical educational qualifications obtained in different countries are valued differently on the US labor market; and selection-related, determining which particular segments of the source country ability distribution are likely to send migrants to the US.

As a first step, I check whether the predicted occupational placement indicators for the two sets of hypothetical individuals, migrating in 1975 and 1985 respectively, are influenced by several quality and selection country specific attributes. The functional form is presented in equation (6).

$$\begin{aligned} &predicted \ln OP_\tau = \alpha' + \beta_1' * GDPpc_\tau + \beta_2' * OPEN_\tau + \beta_3' * ENGLISH_\tau \\ &+ \beta_4' * DIST_\tau + \beta_5' * CONFLICT_\tau + \beta_6' * COM_\tau + \varepsilon_{\tau,t}', \tau = country \end{aligned} \quad (6)$$

The regression is run separately by hypothetical individual and census year for each OP specification (prestige index, education index 1, education index 2). The dependent variables are the levels of performance in 2000 for the 1975 arrivals, and in 1990 for the 1985 arrivals. This means estimating 6 (2 years*3 OP definitions) regressions for the 1975 arrival, and 3 (1 years*3 OP definitions) for the 1985 one.

The explanatory indicators reflect a country's situation around migration time, i.e. during the 1970s decade or its first half for the 1975 arrival, and during the 1980s decade, or its first half, for the 1985 arrival. GDPpc stands for log of per capita-GDP in constant 2000 prices averaged over 1970-1975, and 1980-1985, respectively, and is downloaded from the Penn World Tables (Version 6.2).[39] GDPpc may affect migrants' performance through both quality and selectivity channels. The fact that people coming from high income countries are better off at arrival has been associated with the ease of skill transferability between US and equally developed countries. The coefficient of GDP should have a positive impact, unless selectivity forces trigger a different outcome. OPEN is the ratio of exports plus imports to GDP, and aims at capturing the degree of openness of the economy in the origin country. This variable is also available in the Penn World Tables. The coefficient of Open is expected to be positive provided that a high degree of an economy's openness implies more information is available to prospective migrants. The English dummy in the model is constructed based on CIA – The World Factbook (2002) and takes value 1 if English is the main spoken language in a country. This variable should have a qualitative effect on performance; therefore the sign of the coefficient is expected to be positive. DIST is a selectivity indicator measured as the log of distance in miles to the US[40]. It affects migrants' ability distribution by its influence on migration costs. A country in the proximity of the US has a higher propensity to send unskilled migrants compared to one that is further away. Therefore distance should have a positive impact on the entry level of occupational placement. The presence of military CONFLICT has a negative selection effect. In estimations for the 1975 arrival, military conflict[41] is evaluated for the 1970s decades, whereas estimations for the 1985 arrival use an index based on data for the 1980s. Variable COM[42] indicates whether a country has a communist regime in 1970, and respectively 1985.

The next step is to determine whether country attributes impact on the improvement in occupational placement over a decade. Equations (7) and (6) are equivalent with respect to explanatory variables, but they have different dependent variables.

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[39] Heston, Summers, Aten (2006)
[40] From Andrew Rose datasets available at http://faculty.haas.berkeley.edu/arose
[41] Constructed using www. prio.no, "Armed Conflict Version 2.1" by Gledisch, Wallensteen, Eriksson, Sollenberg and Strand (2004)
[42] Robert Barro's "Religion Adherence Data" http://www.economics.harvard.edu/faculty/barro/data_sets_barro

$$\Delta(\mathit{predicted}\ln OP_{t-(t+10),\tau}) = \alpha^{''} + \beta_1^{''} * GDPpc_\tau + \beta_2^{''} * OPEN_\tau + \beta_3^{''} * ENGLISH_\tau$$
$$+ \beta_4^{''} * DIST_\tau + \beta_5^{''} * CONFLICT_\tau + \beta_6^{''} * COM_\tau + \varepsilon_{\tau,t}^{''}, t = 1980,1990,2000, \tau = country \quad (7)$$

For the 1975 arrival, there are 6 regressions (3 OP definitions * 2 periods over which improvement can be evaluated – between Censuses 1980 and 1990; between Censuses 1990 and 2000). For the 1985 arrival no more than 3 regressions can be run, because the performance of individuals is observed only in 1990 and 2000.

The final specification (equation 8) combines the conditional convergence estimations described in sub-section 4.1 with equation (7), and implies running 6 regressions for the 1975 arrival, and 3 for the 1985 arrival.

$$\Delta(\mathit{predicted}\ln OP_{t-(t+10),\tau}) = \alpha^{'''} + \theta^{'''} * \mathit{predicted}\ln OP_{t,\tau} + \beta_2^{'''} * OPEN_\tau + \beta_4^{'''} * DIST_\tau$$
$$+ \beta_5^{'''} * CONFLICT_\tau + \beta_6^{'''} * COM_\tau + \varepsilon_{\tau,t}^{''}, t = 1980,1990,2000, \tau = country \quad (8)$$

GDP and English are not included in specification (8) because they are correlated to a large degree with the initial predicted occupational placement. Other biases stemming from the strength of the β-convergence, and from the high explanatory power of the country of origin attributes vis-à-vis initial performance (equation 7) will be discussed in more detail in the next section.

5.2. EMPIRICAL RESULTS

The country specific attributes employed to explain the predicted initial occupational placement and the predicted improvement in occupational placement are described in the previous section. Table 6 presents the summary statistics associated with these variables. The set referring to 1980-1989 is assumed to influence the performance of the 1985 arrivals, while the set for period 1970-1979 refers to the 1975 arrivals.

The results of the estimations are presented in Table 7. They are robust to alternative definitions of occupational placement, as shown by Annex tables A2 and A3. The coefficients and standard errors are small because of the log specification of the dependent variable. Columns 1 through 3 and 7 through 9 describe the estimates related to performance during the 1990s of the 1985 and 1975 arrivals. Columns 4 through 6 refer to the performance during the 1980s of the 1975 arrivals.

Columns 1, 4 and 7 use as a dependent variable the predicted initial occupational placement. The results in column 1 confirm findings in Mattoo et al. (2008) according to which country attributes explain a significant part of skilled immigrants' performance level in 1990, provided other things are kept constant. Both qualitative and selection factors have a significant impact in shaping the entry level occupational attainment: GDP per capita is significantly positive, distance to US has the expected positive sign and is significantly different from zero, the conflict variable affects negatively the performance. The English dummy has the right sign but is not significant. The degree of openness of the economy in the origin country and the presence of a communist regime do not seem to matter. Turning to the 1975 arrival, the explanatory power of the regressions is much reduced for the 1980s decade (column 4), and more so for the 1990s (column 5). However, the level of occupational placement in the year closest to the arrival, i.e. 1980, still benefits from positive and significant effect of GDP, as well as from positive effect of the English language.

Columns 2, 5 and 8 present the impact of the same set of country specific attributes on the predicted improvement in the occupational placement. All coefficients are significant except the one for the degree of openness. However, signs are reversed from what is shown in columns 1, 4 and 7. For the 1985 arrival (column 2), the explanatory power is around 63%, the highest when compared to the other two regressions (columns 5 and 8).

Columns 3, 6 and 9 report the results of estimations using both country specific attributes and the initial predicted level of performance to explain predicted improvement. GDP per capita and English are not included in the regressions due to their high correlation (over 40%) with the initial level of performance. As revealed by sub-section 4.2, the initial performance has always a negative and significant effect which is equivalent in magnitude to the β coefficients reported in Table 5. In addition, the signs of the estimates for most country attributes are again in accord to the ones found in columns 1, 4 and 7. Nevertheless the significance levels remain low. However, for the 1985 arrival (column 3) distance to US and communism index are significant.

The significant impact of initial performance accompanied by low significance of country attributes in the same regressions may be interpreted, in light of the findings of conditional convergence described in section 4, as an application of the "skill transferability" mechanism (Chiswick, 1978, Duleep and Regets, 1997). For illustration, consider the case of the 1985 arrival, for which the estimations have significant explanatory power. Countries with higher GDP per capita are found to send migrants that have high initial levels of performance (as revealed by the positive and significant coefficient of GDP in column 1). This can be attributed to the similarity between the US and developed countries, which favors equal or quasi-similar appreciation of the skills of migrants relative to those of natives. Consequently, since migrants from countries with high GDP per capita are already valued at or close to their full potential, there is not much space left for them to improve (this result is mirrored by the negative coefficient between growth and initial performance in column 3). On the other hand, migrants from countries with lower GDP may come with a specific heritage of abilities that is not immediately convertible into skills valued on the US labor market. Therefore, such individuals will not attain highly ranked occupations immediately after migration (their initial performance will be lower as suggested by the positive coefficient of GDP in column 1). However, over time they will experience a higher rate of growth reflecting the gradual recognition of their abilities and motivation on the US market (captured by the negative coefficient of initial performance in column 3).

Although found to be the most important determinant, initial performance does not explain the whole variation in the assimilation patterns. Individuals may start from the same point, but have different growth rates. Indeed, Figure 2 shows how a migrant born in Mexico and one born in Uruguay have roughly the same initial occupational placement in 1990, but their predicted improvements differ to a large degree. This could be associated with a qualitative difference most likely related to selection, which in turn is determined by selection-related country attributes. As a confirmation, column 3 finds distance to the US to have a negative and significant effect on growth. Intuitively, migrants coming from distant (not so distant) countries are likely to be positively (negatively) selected from the ability distribution of the origin countries. Mexico's proximity to the US would thus explain the difference in placement improvement between Mexican migrants and those from Uruguay. Additionally, the positive and significant effect of the communism index could reflect the higher motivation for migrants that do not have the option to return to their countries of origin.

6. CONCLUSIONS

This study investigates how patterns in occupational placement of skilled male immigrants on the US labor market vary over time and by country of origin when education and other human capital characteristics are kept constant. By focusing on occupational placement rather than earnings, the analysis reaps the former's benefit of better comparability across regions and in time.

Employing three US Census samples, 1980, 1990, and 2000, to follow the progress of cohorts who arrived during the 1970s and 1980s, it is found that both initial occupational placements by country and improvements in occupational placements within the first 10 or 20 years since arrival are highly heterogeneous. Furthermore, immigrants from countries with a low initial occupational placement are shown to progress faster than those from countries with better placement around migration time. Nevertheless, the magnitude of the convergence factor is not large enough to insure full catch-up within one or two decades since arrival of countries that started with lower performances to the levels of those which started at an advantage.

Country specific attributes have both qualitative and selection effects on the predicted initial occupational placement. However, their impact on predicted occupational placement improvement over a decade seems to be indirect, in the sense that it is channeled through the initial levels of performance which are shown to be negatively correlated with the growth rate. Once initial occupational placement is introduced in the estimation explaining the predicted improvement in occupational placement, most country specific variables change signs and lose significance.

The findings in this paper may have several policy implications. On the US labor market, migrants would benefit most from reduced legal and professional barriers in practicing occupations for which they acquired nominal qualifications before arrival. If migrants' well-being is of concern for the host country regulators, the latter could cooperate with origin countries to eliminate such barriers in excess of what is reasonably justified. One reason why US policy makers would want to favor harmonization could be the necessity to protect less skilled natives against competition from highly skilled migrants who are engaged in low skilled occupations for a long period of time (Kim, 2009a). As another practical implication, information about migrants' professional achievement abroad could benefit policy makers in origin countries by helping them allocate education resources in a more efficient way. On this line, Mattoo et al. (2008) suggest promoting private rather than public funding for the education of potential migrants, while keeping public resources for institutions preparing students for the domestic labor market.

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8. TABLES AND CHARTS

Table 1. Characteristics of the hypothetical individuals:

	(1)	(2)
Year of arrival	1975	1985
Age at arrival	25	25
Level of education	At least college degree	At least college degree
Age as of Census 1980	30	-
Age as of Census 1990	40	30
Age as of Census 2000	50	40

Table 2. Summary Statistics of Datasets Extracted from the US Census Samples

	DECADE 1970-1979			DECADE 1980-1989	
	Census 1980	**Census 1990**	**Census 2000**	**Census 1990**	**Census 2000**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Individuals in the sample (unweighted)	41,234	39,445	35,880	75,851	78,745
Total number of people (after weighting)	824,680	847,573	750,289	1,668,342	1,704,575
Age interval	16-40	26-50	36-60	16-50	26-60
Median age	30	40	49	32	41
Years since arrival	1970-1974			1980-1984	
six to ten	41%	40%	38%	47%	43%
	1975-1979			1985-1989	
one to five	59%	60%	62%	53%	57%
By education:					
None or preschool	4%	7%	8%	8%	6%
Grade 1, 2, 3, or 4	9%	9%	7%	6%	4%
Grade 5, 6, 7, or 8	25%	20%	21%	17%	19%
Grade 9	5%	5%	4%	6%	6%
Grade 10	4%	3%	2%	3%	3%
Grade 11	4%	2%	2%	3%	2%
Grade 12	19%	20%	21%	23%	24%
1 to 3 years of college	9%	13%	13%	13%	14%
4+ years of college	21%	21%	22%	21%	21%

Table 3 Means of Alternative Occupational Placement Indices, by level of education and year

	Prestige Index			Education Index 1			Education Index 2		
	1980	1990	2000	1980	1990	2000	1980	1990	2000
None or preschool	31	32	33	18	28	31	11.1	11.7	11.9
Grade 1, 2, 3, or 4	31	31	32	16	26	29	11.0	11.5	11.7
Grade 5, 6, 7, or 8	32	32	33	17	27	31	11.1	11.7	11.9
Grade 9	33	32	34	19	28	33	11.3	11.8	12.1
Grade 10	33	33	35	21	30	35	11.4	12.0	12.3
Grade 11	34	33	35	22	31	35	11.6	12.0	12.3
Grade 12	37	35	36	26	36	39	11.8	12.4	12.6
1 to 3 years of college	41	40	42	36	47	53	12.5	13.1	13.4
4+ years of college	55	54	56	62	72	78	14.2	14.8	15.1

Table 4. Estimates Based on Equation (1)

EDUCATION INDEX 1	DECADE: 1970-1979			DECADE: 1980-1989	
VARIABLES	**CENSUS 1980**	**CENSUS 1990**	**CENSUS 2000**	**CENSUS 1990**	**CENSUS 2000**
Age	0.00316	0.00684	-0.0069	0.00884***	0.00568***
	[0.00410]	[0.00482]	[0.00624]	[0.00163]	[0.00207]
Age squared	0.0000214	-0.000106*	0.0000401	-0.000113***	-9.29e-05***
	[0.0000700]	[0.0000610]	[6.32e-05]	[2.38e-05]	[2.37e-05]
Years since arrival (dummy with value 1 for second half of the decade)	-0.0596***	-0.0300***	-0.0352***	-0.0413***	-0.0317***
	[0.00573]	[0.00490]	[0.00502]	[0.00344]	[0.00332]
EDUCATION DUMMIES					
five to nine years of education	0.00444	0.0231***	0.0382***	-0.000464	0.0201***
	[0.00705]	[0.00646]	[0.00697]	[0.00491]	[0.00531]
ten to twelve years of education	0.0566***	0.0646***	0.0866***	0.0195***	0.0606***
	[0.00933]	[0.00874]	[0.00969]	[0.00571]	[0.00604]
high-school level	0.168***	0.173***	0.191***	0.109***	0.146***
	[0.00974]	[0.00836]	[0.00860]	[0.00564]	[0.00576]
some college	0.451***	0.419***	0.430***	0.317***	0.380***
	[0.0134]	[0.0105]	[0.0107]	[0.00735]	[0.00712]
Bachelor's Degree or higher	1.011***	0.825***	0.826***	0.700***	0.746***
	[0.0123]	[0.0101]	[0.0103]	[0.00740]	[0.00702]
Constant	5.610***	5.654***	6.056***	5.950***	6.015***
	[0.189]	[0.181]	[0.221]	[0.0785]	[0.0828]
Observations	41234	39445	35880	75851	78745
Country fixed effects	yes	yes	yes	yes	yes
R-squared	0.51	0.51	0.51	0.49	0.48

*** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in brackets

Figure 1. Predicted Occupational Placement in 1990, 1985 arrival

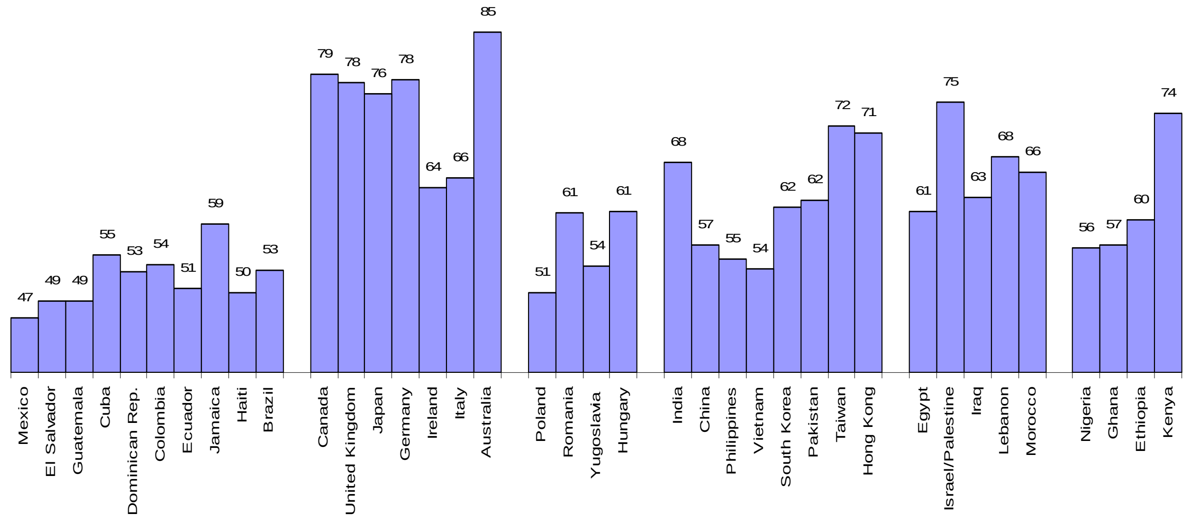


Figure 2 Predicted Occupational Placement Improvement (ΔÔP) versus Predicted Occupational Placement (ÔP), 1985 arrival

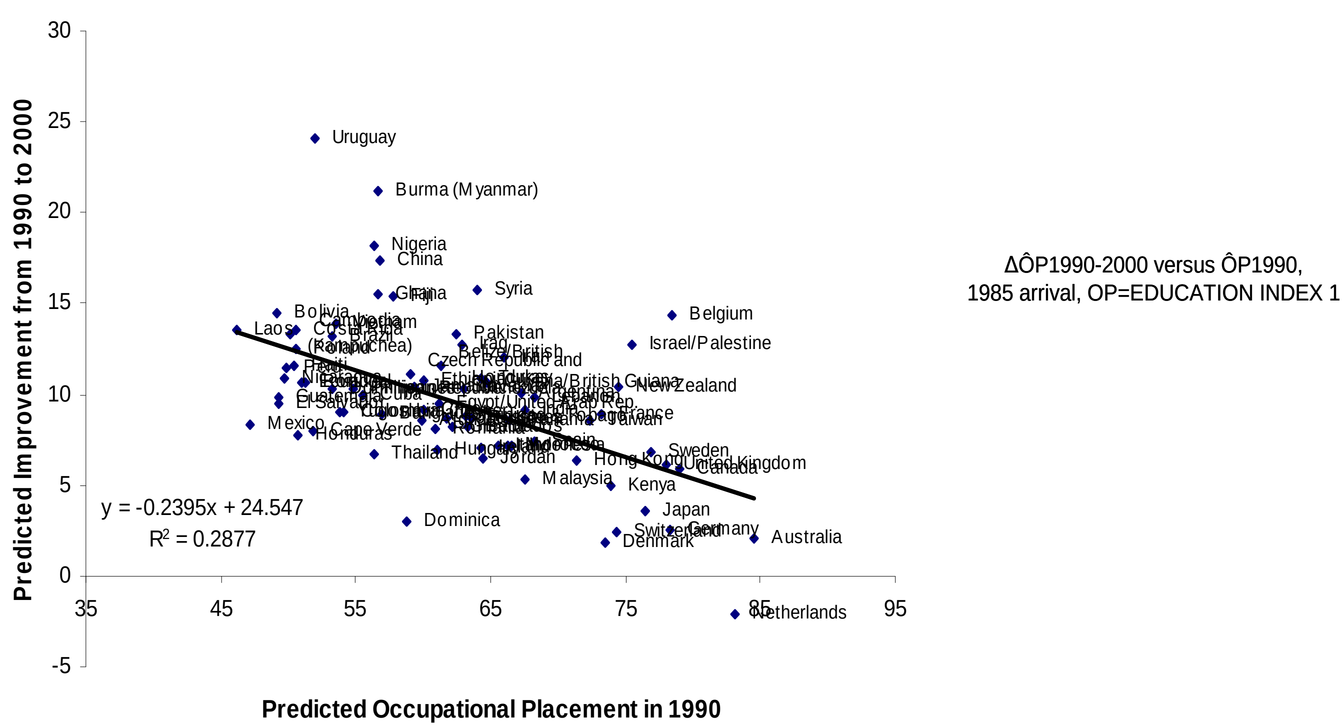
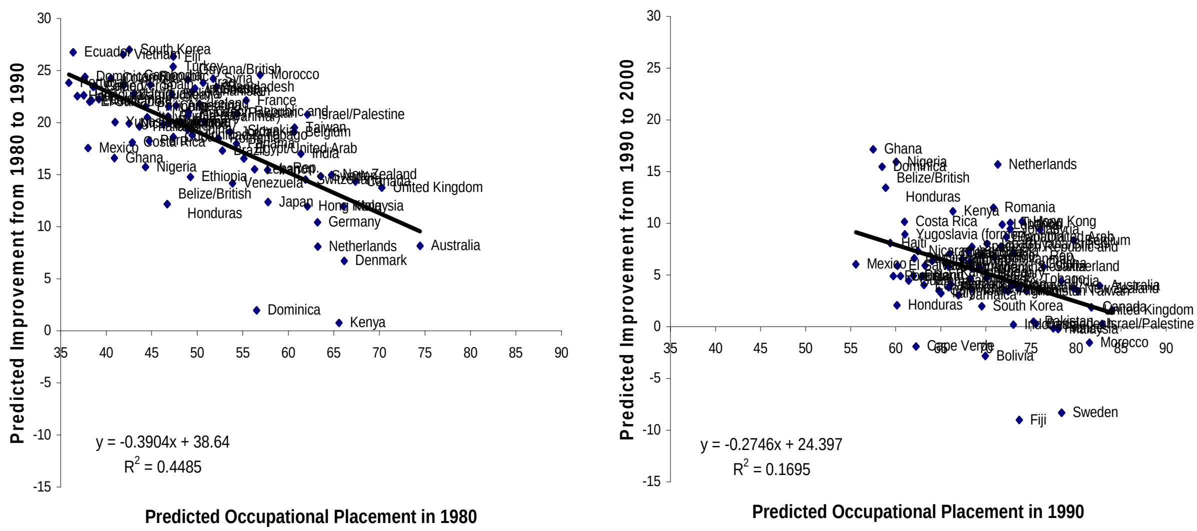


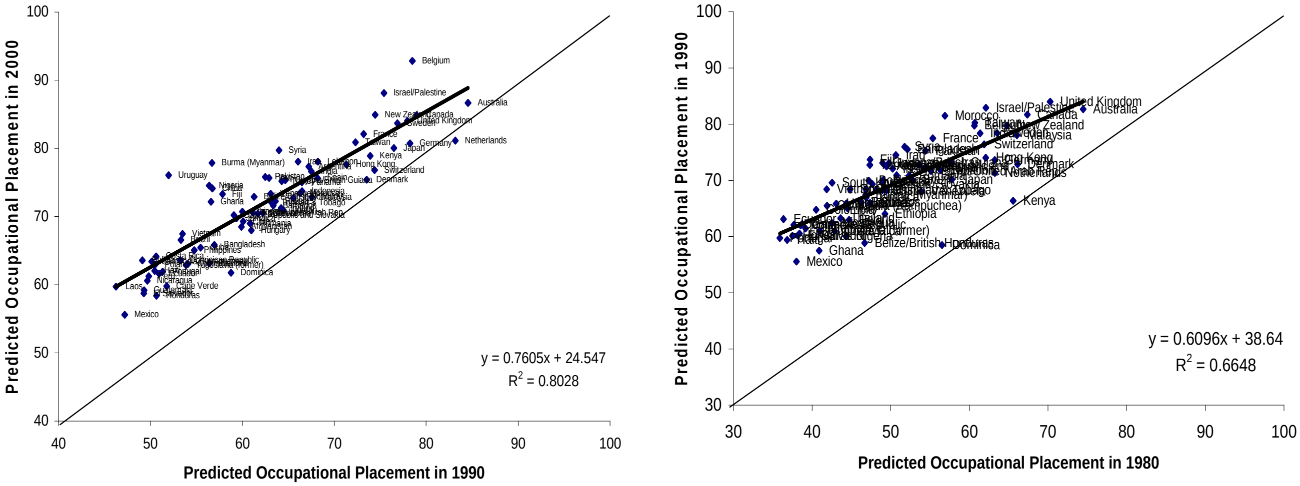
Figure 3 Predicted Occupational Placement Improvement (ΔÔP) versus Predicted Occupational Placement (ÔP), 1975 arrival



a. ΔÔP1980-1990 versus ÔP1980,
1975 arrival, OP=EDUCATION INDEX 1

b. ΔÔP1990-2000 versus ÔP1990,
1975 arrival, OP=EDUCATION INDEX 1

Figure 4 Predicted Occupational Placement (ÔP) in 2000/1990 versus Predicted Occupational Placement (ÔP) in 1990/1980, 1985/1975 arrival



a. ÔP2000 versus ÔP1990, 1985 arrival, OP=EDUCATION INDEX 1

b. ÔP1990 versus ÔP1980, 1975 arrival, OP=EDUCATION INDEX 1

Figure 5 Predicted Occupational Placement Improvement (ΔÔP) versus Predicted Occupational Placement (ÔP), 1985 arrival, OP=Education Index 1, corrected sample

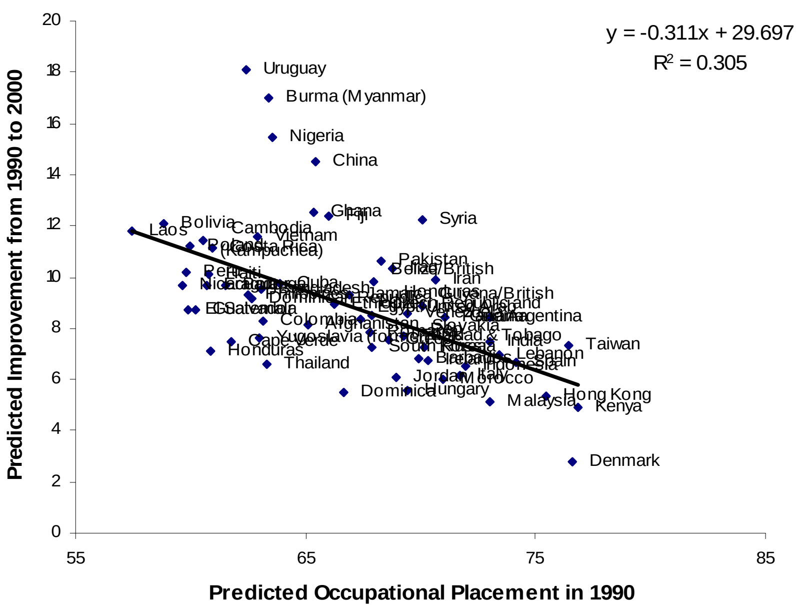
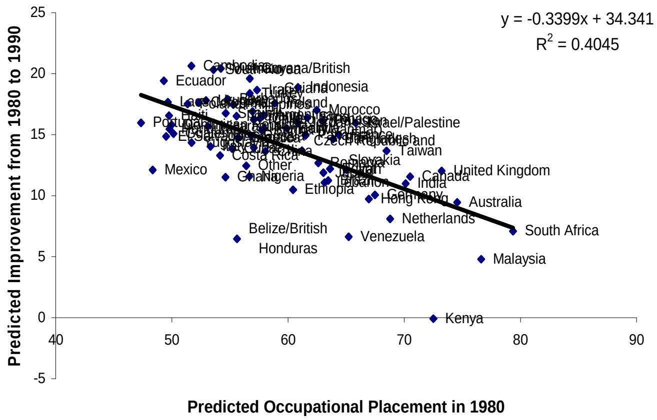
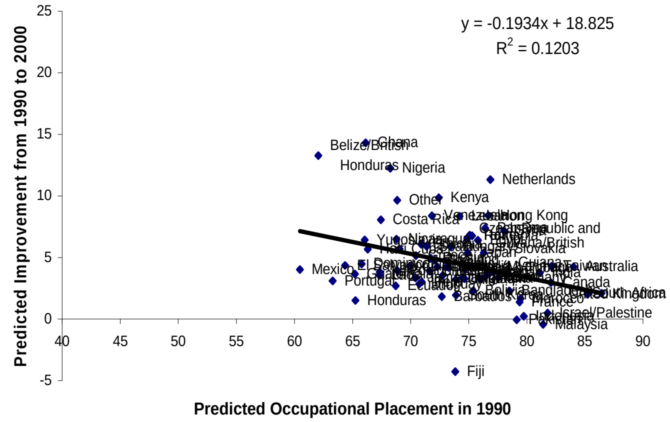


Figure 6 Predicted Occupational Placement Improvement (ΔÔP) versus Predicted Occupational Placement (ÔP), 1975 arrival, OP=Education Index 1, based on Pseudo-Panel Estimation



a. ΔÔP1980 versus ÔP1990,
1975 arrival, EDUCATION INDEX 1



b. ΔÔP2000 versus ÔP1990,
1975 arrival, EDUCATION INDEX 1

c. ÔP1980 versus ÔP1990,
1975 arrival, EDUCATION INDEX 1

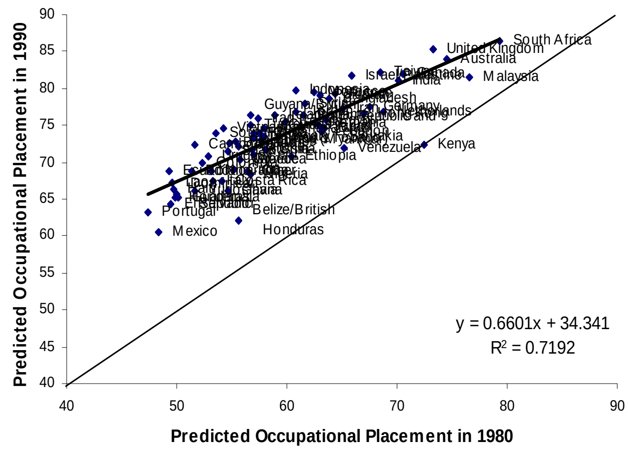


Table 5. Results from estimating β-convergence models

	1985 arrival	1975 arrival		
	1990-2000	1980-1990	1980-2000	1990-2000
	(1)	(2)	(3)	(4)
	EDUCATION INDEX 1			
Predicted Log of OP in 1990	-0.0291***			-0.0278***
	[0.00522]			[0.00726]
Predicted Log of OP in 1980		-0.0523***	-0.0297***	
		[0.00442]	[0.00166]	
Constant	0.202***	0.359***	0.205***	0.189***
	[0.0341]	[0.0281]	[0.0105]	[0.0481]
Observations	79	80	80	80
R-squared	0.554	0.834	0.906	0.343
	PRESTIGE INDEX			
Predicted Log of OP in 1990	-0.0290***			-0.0183**
	[0.00377]			[0.00706]
Predicted Log of OP in 1980		-0.0341***	-0.0177***	
		[0.00566]	[0.00210]	
Constant	0.188***	0.218***	0.114***	0.118***
	[0.0236]	[0.0353]	[0.0132]	[0.0447]
Observations	79	80	80	80
R-squared	0.562	0.419	0.546	0.178
	EDUCATION INDEX 2			
Predicted Log of OP in 1990	-0.0234***			-0.0198***
	[0.00492]			[0.00677]
Predicted Log of OP in 1980		-0.0382***	-0.0214***	
		[0.00469]	[0.00172]	
Constant	0.0660***	0.107***	0.0603***	0.0552***
	[0.0133]	[0.0125]	[0.00457]	[0.0184]
Observations	79	80	80	80
R-squared	0.414	0.647	0.773	0.213

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 6 Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
1980-1989					
Log of GDP per capita	71	8.52	0.95	6.05	10.09
Openness Index	71	50.91	31.11	7.53	142.98
Log of Distance to the US	71	8.45	0.55	6.98	9.15
English	71	0.41	0.50	0.00	1.00
Military conflict	71	0.38	0.49	0.00	1.00
Communism index	71	0.14	0.35	0.00	1.00
1970-1979					
Log of GDP per capita	72	8.34	0.93	6.20	10.01
Openness Index	72	51.10	36.09	7.16	189.99
Log of Distance to the US	72	8.43	0.56	6.98	9.15
English	72	0.42	0.50	0.00	1.00
Military conflict	72	0.40	0.49	0.00	1.00
Communism index	72	0.07	0.26	0.00	1.00

Table 7 OLS Estimations based on country specific variables

	1985 arrival			1975 arrival					
EDUCATION INDEX 1	**1990-2000**			**1980-1990**			**1990-2000**		
	predicted ($lnOP_{1990}$)	**Δpredicted ($lnOP_{1990-2000}$)**	**(1/10) Δpredicted ($lnOP_{1990-2000}$)**	**predicted ($lnOP_{1980}$)**	**Δpredicted ($lnOP_{1980-1990}$)**	**(1/10) Δpredicted ($lnOP_{1980-1990}$)**	**predicted ($lnOP_{1990}$)**	**Δpredicted ($lnOP_{1990-2000}$)**	**(1/10) Δpredicted ($lnOP_{1990-2000}$)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Log of GDP per capita	**0.112*** [0.0205]**	**-0.0432*** [0.00841]**		**0.0999** [0.0500]**	**-0.0493* [0.0273]**		0.0369 [0.0227]	**-0.0208** [0.00886]**	
Openness Index	-0.00006 [0.000650]	0.00015 [0.000257]	0.00001 [1.69e-05]	-0.00019 [0.00124]	-0.00004 [0.000703]	-0.00002 [2.38e-05]	-0.00015 [0.000684]	0.00025 [0.000299]	0.00001 [2.61e-05]
Log of Distance to the US	**0.142*** [0.0463]**	**-0.0229*** [0.00724]**	**0.00258*** [0.000895]**	0.0923 [0.0623]	-0.0278 [0.0311]	0.00272 [0.00198]	**0.0913** [0.0443]**	**-0.0239** [0.0117]**	0.000705 [0.00113]
English	0.0566 [0.0446]	**-0.0220** [0.0108]**		**0.123* [0.0731]**	-0.0317 [0.0408]		0.0393 [0.0422]	-0.0136 [0.0108]	
Military conflict	**-0.0977** [0.0464]**	**0.0222* [0.0126]**	-0.000152 [0.00129]	-0.00147 [0.127]	-0.0196 [0.0776]	-0.00133 [0.00214]	-0.0358 [0.0508]	0.00546 [0.0147]	0.000404 [0.00163]
Communism index	-0.0399 [0.0733]	**0.0414** [0.0205]**	**0.00458* [0.00242]**	0.0406 [0.152]	-0.0327 [0.0876]	-0.00267 [0.00238]	-0.0353 [0.0697]	0.0123 [0.0191]	0.00166 [0.00207]
Predicted Log of OP in 1990			**-0.0285*** [0.00419]**						**-0.0280*** [0.00938]**
Predicted Log of OP in 1980						**-0.0519*** [0.00460]**			
Constant	4.291*** [0.454]	0.699*** [0.103]	0.175*** [0.0226]	4.583*** [0.672]	0.987*** [0.320]	0.335*** [0.0279]	5.494*** [0.431]	0.432*** [0.144]	0.184*** [0.0563]
Observations	71	71	71	72	72	72	72	72	72
R-squared	0.637	0.639	0.695	0.282	0.142	0.844	0.221	0.163	0.377

***** p<0.01, ** p<0.05, * p<0.1**
Robust standard errors in brackets

9. ANNEX

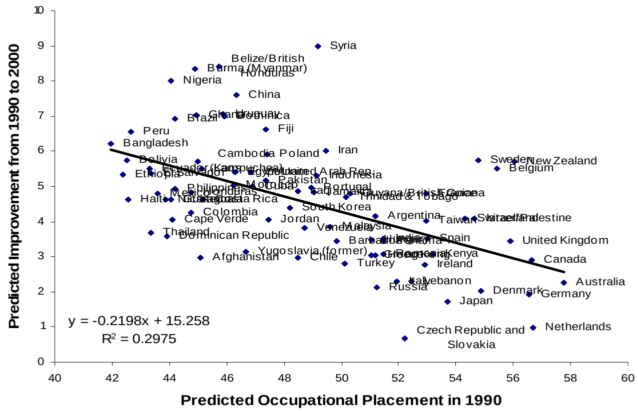
Table A1 Estimates Based on Equation (1)

a. PRESTIGE INDEX	DECADE: 1970-1979			DECADE: 1980-1989	
	CENSUS 1980	CENSUS 1990	CENSUS 2000	CENSUS 1990	CENSUS 2000
Age	0.0170***	0.00514	-0.0109**	0.0127***	0.00411***
	[0.00230]	[0.00320]	[0.00436]	[0.00113]	[0.00142]
Age squared	-0.000218***	-0.0000787*	7.94e-05*	-0.000172***	-7.58e-05***
	[0.0000386]	[0.0000405]	[4.43e-05]	[1.64e-05]	[1.64e-05]
Years since arrival (dummy with value 1 for second half of the decade)	-0.0415***	-0.0260***	-0.0254***	-0.0331***	-0.0204***
	[0.00299]	[0.00328]	[0.00357]	[0.00231]	[0.00229]
EDUCATION DUMMIES					
five to nine years of education	0.0285***	0.0282***	0.0311***	0.00750**	0.0142***
	[0.00420]	[0.00438]	[0.00486]	[0.00357]	[0.00368]
ten to twelve years of education	0.0593***	0.0492***	0.0555***	0.0173***	0.0388***
	[0.00515]	[0.00565]	[0.00640]	[0.00397]	[0.00407]
high-school level	0.0978***	0.0854***	0.0914***	0.0508***	0.0639***
	[0.00513]	[0.00526]	[0.00571]	[0.00378]	[0.00384]
some college	0.194***	0.202***	0.209***	0.146***	0.179***
	[0.00657]	[0.00638]	[0.00703]	[0.00461]	[0.00461]
Bachelor's Degree or higher	0.453***	0.476***	0.515***	0.389***	0.447***
	[0.00636]	[0.00679]	[0.00734]	[0.00492]	[0.00484]
Constant	5.636***	5.683***	6.304***	5.809***	5.987***
	[0.0815]	[0.129]	[0.134]	[0.0526]	[0.0917]
Observations	41234	39445	35880	75851	78745
Country fixed effects	yes	yes	yes	yes	yes
R-squared	0.41	0.40	0.40	0.37	0.36

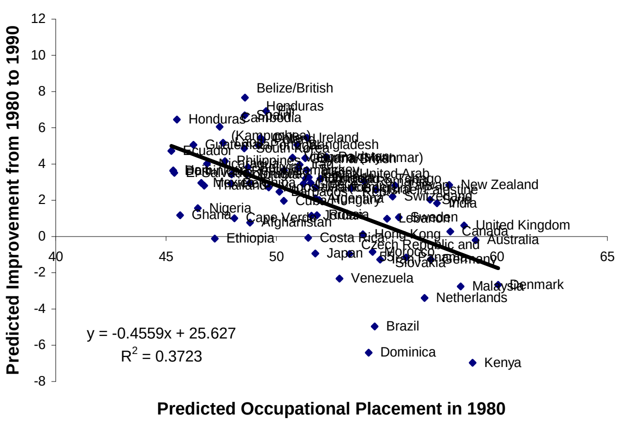
b. EDUCATION INDEX 2	DECADE: 1970-1979			DECADE: 1980-1989	
	CENSUS 1980	CENSUS 1990	CENSUS 2000	CENSUS 1990	CENSUS 2000
Age	0.00140*	0.00141	-0.00202	0.00236***	0.00163***
	[0.000723]	[0.00105]	[0.00147]	[0.000351]	[0.000479]
Age squared	-0.00000958	-0.0000216	1.31E-05	-3.20e-05***	-2.61e-05***
	[0.0000125]	[0.0000134]	[1.49e-05]	[5.17e-06]	[5.52e-06]
Years since arrival (dummy with value 1 for second half of the decade)	-0.0107***	-0.00742***	-0.00919***	-0.00912***	-0.00682***
	[0.00103]	[0.00109]	[0.00119]	[0.000749]	[0.000776]
EDUCATION DUMMIES					
five to nine years of education	0.00856***	0.00895***	0.0134***	0.00168	0.00811***
	[0.00116]	[0.00138]	[0.00163]	[0.00104]	[0.00124]
ten to twelve years of education	0.0190***	0.0191***	0.0252***	0.00848***	0.0188***
	[0.00151]	[0.00178]	[0.00218]	[0.00116]	[0.00136]
high-school level	0.0364***	0.0403***	0.0474***	0.0262***	0.0369***
	[0.00160]	[0.00171]	[0.00193]	[0.00115]	[0.00130]
some college	0.0844***	0.0917***	0.101***	0.0689***	0.0888***
	[0.00229]	[0.00218]	[0.00244]	[0.00152]	[0.00161]
Bachelor's Degree or higher	0.204***	0.201***	0.215***	0.167***	0.192***
	[0.00229]	[0.00229]	[0.00250]	[0.00166]	[0.00169]
Constant	2.489***	2.473***	2.586***	2.549***	2.556***
	[0.0350]	[0.0489]	[0.0526]	[0.0178]	[0.0224]
Observations	41234	39445	35880	75851	78745
Country fixed effects	yes	yes	yes	yes	yes
R-squared	0.546	0.538	0.53	0.52	0.51

*** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in brackets

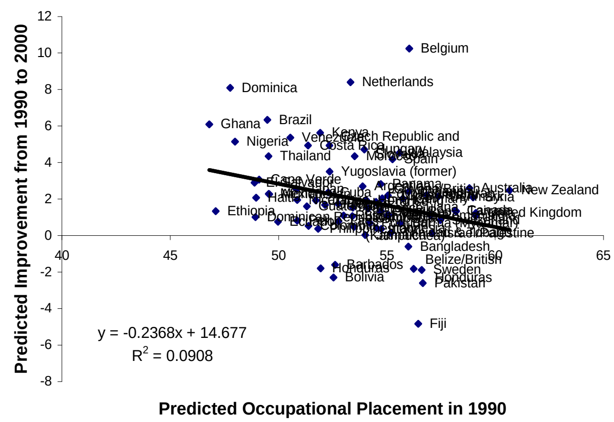
Figure A1 Predicted Occupational Placement Improvement (ΔÔP) versus Predicted Occupational Placement (ÔP), PRESTIGE INDEX



a. ΔÔP1990-2000 versus ÔP1990,
1985 arrival, OP=PRESTIGE INDEX

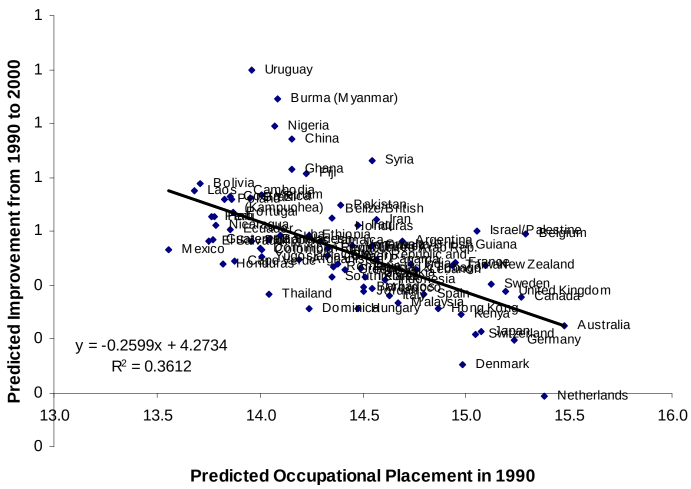


b. ΔÔP1980-1990 versus ÔP1980,
1975 arrival, OP=PRESTIGE INDEX

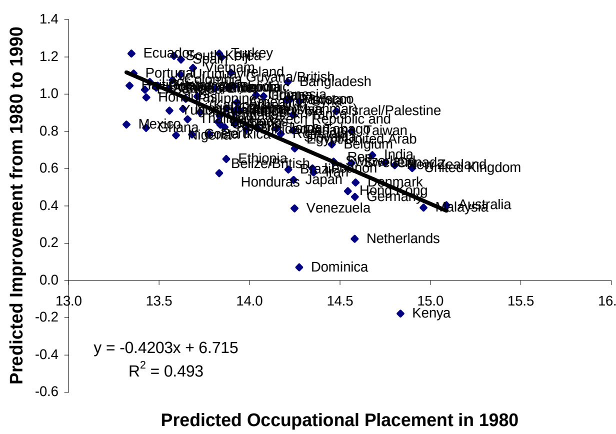


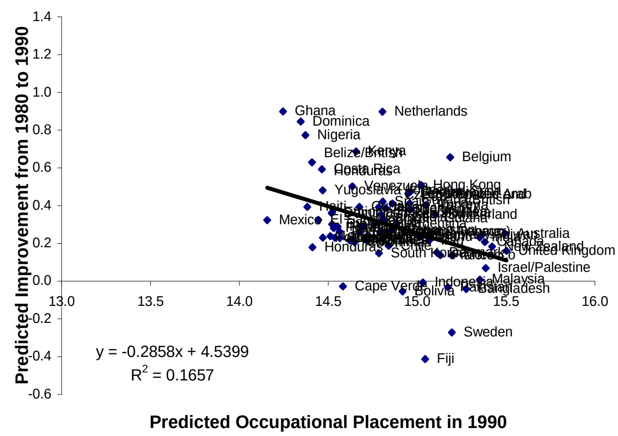
c. ΔÔP1990-2000 versus ÔP1990,
1975 arrival, OP=PRESTIGE INDEX

Figure A2 Predicted Occupational Placement Improvement (ΔÔP) versus Predicted Occupational Placement (ÔP), EDUCATION INDEX 2



a. ΔÔP1990-2000 versus ÔP1990, 1985 arrival, OP=EDUCATION INDEX 2

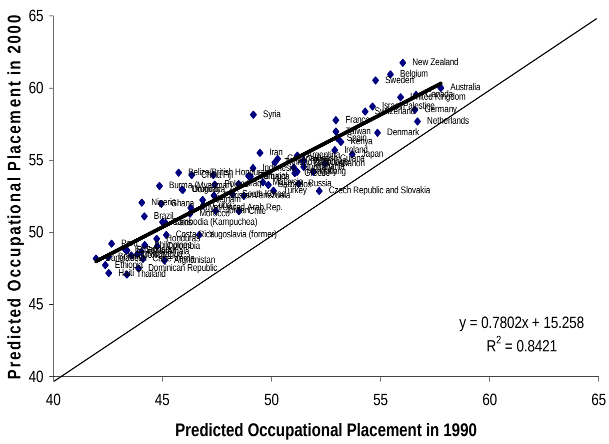




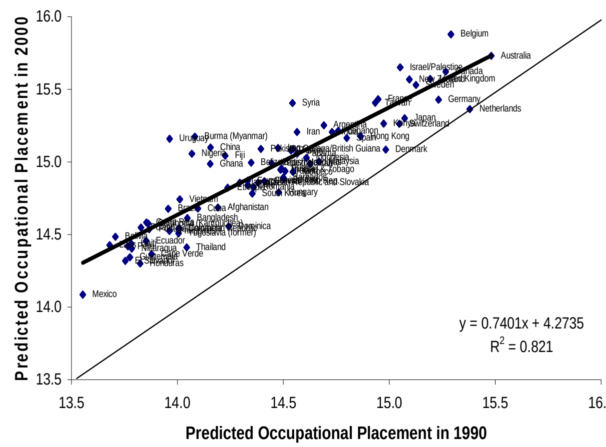
b. ΔÔP1980-1990 versus ÔP1980, 1975 arrival, OP=EDUCATION INDEX 2

c. ΔÔP1990-2000 versus ÔP1990, 1975 arrival, OP=EDUCATION INDEX 2

Figure A3 Predicted Occupational Placement (ÔP) in 2000 versus Predicted Occupational Placement (ÔP) in 1990, 1985 arrival



a. ÔP2000 versus ÔP1990,
1985 arrival, PRESTIGE INDEX



b, ÔP2000 versus ÔP1990,
1985 arrival, OP=EDUCATION INDEX 2

Table A2 OLS Estimations based on country specific variables

	1985 arrival			1975 arrival					
PRESTIGE INDEX	1990-2000			1980-1990			1990-2000		
	predicted (lnOP$_{1990}$)	Δpredicted (lnOP$_{1990-2000}$)	(1/10) Δpredicted (lnOP$_{1990-2000}$)	predicted (lnOP$_{1980}$)	Δpredicted (lnOP$_{1980-1990}$)	(1/10) Δpredicted (lnOP$_{1980-1990}$)	predicted (lnOP$_{1990}$)	Δpredicted (lnOP$_{1990-2000}$)	(1/10) Δpredicted (lnOP$_{1990-2000}$)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log of GDP per capita	0.0681*** [0.0130]	-0.0222*** [0.00571]		0.0344 [0.0212]	-0.0179* [0.00936]		0.0126 [0.0147]	-0.00309 [0.00460]	
Openness Index	-0.00018 [0.000431]	0.00026 [0.000188]	0.00002 [1.05e-05]	-0.00017 [0.000643]	-0.00006 [0.000275]	-0.00002 [2.19e-05]	-0.00028 [0.000500]	0.00012 [0.000150]	0.00001 [1.42e-05]
Log of Distance to the US	0.0610*** [0.0218]	-0.0128** [0.00552]	0.000740* [0.000406]	0.023 [0.0256]	-0.0077 [0.0112]	0.000924 [0.000834]	0.0395* [0.0233]	-0.00532 [0.00569]	0.000242 [0.000525]
English	0.0399 [0.0247]	-0.0128 [0.00783]		0.0559* [0.0325]	0.0109 [0.0150]		0.0318 [0.0260]	-0.0063 [0.00615]	
Military conflict	-0.0692** [0.0285]	0.0125 [0.00841]	-0.000638 [0.000782]	0.00504 [0.0525]	-0.00659 [0.0230]	0.00039 [0.00136]	-0.0212 [0.0353]	-0.00802 [0.00814]	-0.00113 [0.000891]
Communism index	0.0218 [0.0304]	0.0148 [0.0138]	0.00243** [0.00117]	0.0241 [0.0489]	0.0049 [0.0275]	0.0000863 [0.00174]	-0.0174 [0.0449]	0.000972 [0.0101]	-0.0000822 [0.000838]
Predicted Log of OP in 1990			-0.0279*** [0.00378]						-0.0188** [0.00864]
Predicted Log of OP in 1980						-0.0339*** [0.00503]			
Constant	5.101*** [0.221]	0.377*** [0.0701]	0.175*** [0.0216]	5.747*** [0.301]	0.255* [0.132]	0.209*** [0.0304]	5.866*** [0.226]	0.101 [0.0747]	0.119** [0.0522]
Observations	71	71	71	72	72	72	72	72	72
R-squared	0.649	0.525	0.672	0.203	0.157	0.463	0.153	0.059	0.217

*** p<0.01, ** p<0.05, * p<0.1
Robust standard errors in brackets

Table A3 OLS Estimations based on country specific variables

	1985 arrival			1975 arrival					
EDUCATION INDEX 2	**1990-2000**			**1980-1990**			**1990-2000**		
	predicted ($lnOP_{1990}$)	**Δpredicted ($lnOP_{1990-2000}$)**	**(1/10) Δpredicted ($lnOP_{1990-2000}$)**	**predicted ($lnOP_{1980}$)**	**Δpredicted ($lnOP_{1980-1990}$)**	**(1/10) Δpredicted ($lnOP_{1980-1990}$)**	**predicted ($lnOP_{1990}$)**	**Δpredicted ($lnOP_{1990-2000}$)**	**(1/10) Δpredicted ($lnOP_{1990-2000}$)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Log of GDP per capita	**0.0249***** **[0.00496]**	**-0.00882***** **[0.00194]**		0.0151 [0.00974]	-0.0064 [0.00427]		0.00577 [0.00571]	**-0.00333*** **[0.00185]**	
Openness Index	-0.00003 [0.000155]	0.00004 [5.42e-05]	0.00000 [4.02e-06]	-0.00006 [0.000256]	-0.00001 [0.000116]	-0.00001 [5.85e-06]	-0.00007 [0.000175]	0.00008 [6.14e-05]	0.00001 [6.23e-06]
Log of Distance to the US	**0.0303***** **[0.0111]**	**-0.00408***** **[0.00144]**	**0.000468**** **[0.000206]**	0.0144 [0.0118]	-0.00305 [0.00438]	0.000449 [0.000394]	**0.0185*** **[0.0105]**	**-0.00376*** **[0.00210]**	0.0000983 [0.000251]
English	0.0132 [0.0105]	**-0.00479**** **[0.00224]**		0.0233 [0.0144]	-0.00149 [0.00618]		0.00911 [0.0107]	-0.0026 [0.00213]	
Military conflict	**-0.0239**** **[0.0111]**	0.00371 [0.00261]	-0.0000189 [0.000333]	0.000991 [0.0248]	-0.00359 [0.0119]	-0.000136 [0.000450]	-0.00811 [0.0135]	-0.00097 [0.00308]	-0.000082 [0.000389]
Communism index	-0.00533 [0.0164]	**0.00925**** **[0.00457]**	**0.00124**** **[0.000618]**	0.00645 [0.0260]	-0.00408 [0.0121]	-0.000495 [0.000491]	-0.0112 [0.0169]	0.00146 [0.00351]	0.000246 [0.000427]
Predicted Log of OP in 1990			**-0.0216***** **[0.00439]**						**-0.0197**** **[0.00913]**
Predicted Log of OP in 1980						**-0.0383***** **[0.00478]**			
Constant	2.204*** [0.110]	0.144*** [0.0227]	0.0572*** [0.0105]	2.389*** [0.132]	0.138*** [0.0487]	0.103*** [0.0121]	2.502*** [0.102]	0.0754** [0.0288]	0.0541** [0.0236]
Observations	71	71	71	72	72	72	72	72	72
R-squared	0.617	0.621	0.579	0.216	0.089	0.669	0.167	0.109	0.248

***** p<0.01, ** p<0.05, * p<0.1**
Robust standard errors in brackets